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PATTERN IDENTIFICATION BY MAN AND MACHINE

Proceedings of a Planning Conference
Held At
Texas Christian University
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HUMAN ENGINEERING LABORATORIES

ABERDEEN PROVING GROUND, MARYLAND

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PREFACE

The Institute for the Study of Cognitive Systems at Texas Christian University is conducting a research program titled "Parameters of Human Pattern Perception" with Project THEMIS funding. This program's goals include development of a formal mathematical model of human pattern recognition behavior and subsequent computer simulation of the model. The general approach involves studies of perception using patterns having features representative of the real world. It is anticipated that development and simulation of a model of the behavior of the world's best pattern recognizer -- man -- will produce considerable technological fallout in the areas of machine pattern recognition and computer simulation.

Research on human pattern recognition has become increasingly more sophisticated during the past decade. At the same time substantial progress has been made in duplicating certain aspects of human pattern recognition capability in machines. Cross-fertilization between these two areas is a much-desired goal and the Texas Christian University research program is specifically planned to foster such mutual facilitation. The Institute, under the sponsorship of the U. S. Army Human Engineering Laboratories, is planning a symposium which will bring together leading workers in both fields.

To maximize the benefits of such a symposium to the Department of Defense, a planning conference was held in Fort Worth, Texas, 12-13 December 1968. This conference provided an interface for discussions between basic research on human and machine pattern recognition and the technical requirements of the Army and Defense Department. The Chairman and Discussant for this planning conference was Dr. Earl Alluisi of the University of Louisville, a scientist with many years of experience in military psychology. Representatives of nine Defense agencies gave presentations and/or discussed military requirements for information in this area, and five papers were presented by Institute staff members.

This report summarizes presentations given at the planning conference. All participants agreed that a very useful exchange of ideas and information ensued from this planning conference, and general plans for a substantive symposium have evolved as a result.

David C. Hodge
THEMIS Technical Monitor
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AN OVERVIEW OF HUMAN AND MACHINE PATTERN RECOGNITION

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As an introduction to this conference I would like to attempt a discussion of human and machine pattern recognition in terms of broad perspective and general principles. Let me begin by considering what is meant by pattern recognition.

The term recognition is not particularly apt, because its standard meaning does not fully represent the process. By conventional usage in this context, the term recognition has come to denote the detection or selection of something which merits classification, and the assignment of it to one of a set of predetermined classes. The word pattern, however, is a well chosen term. It was chosen originally to distinguish pattern recognition from the simpler case in which the things to be identified are, within each class, virtually identical.

In pattern recognition the things which must be assigned to the same class are distinguishably different, possibly quite different. Humans perform many such classification tasks well, and they are likely to explain their performance by saying that things which are assigned to the same class exhibit the same pattern. In some such cases humans may be able to indicate what they mean by a pattern. When they can, it usually appears that a pattern consists of a set of features which partially describe each member of the pattern class. Automatic pattern recognition is intended to duplicate this process, and in both cases certain characteristics may be noted:

1. There are data sets which are somehow appropriately delimited. For example, when a human recognizes a tank in a photograph, he has first selected a particular region which is appropriate in that it can be treated as a single unit, a "thing".

2. Each data set is to be assigned to some class.

3. Data sets to be assigned to the same class may be expected to differ in non-trivial ways.

4. Assignment is based on the abstraction of well chosen measures (variously termed features, characteristics,

attributes, descriptors, etc.) which exhibit at least a statistical association with the identification classes.

5. If the measures are imperfectly correlated with class membership, the classification process must use some method, such as statistical decision theory, which is tolerant of imperfection.

These, I think, are the essential characteristics of pattern recognition, but it is of interest to note that they describe a class of activities considerably more inclusive than the term pattern recognition usually denotes. These characteristics not only apply to such obvious pattern recognition problems as the identification of visual imagery, the identification of sound sources, or the classification of data produced by some specialized transducing instrument, but they also include such tasks as medical diagnosis and the recognition, or classification, of military situations.

Medical diagnosis and situation recognition, of course, are not generally regarded as examples of pattern recognition. This implied distinction probably results from the fact that these classification processes are not regarded as operating on raw environmental data, that is, data represented in the form of transducers which respond to energy exchanges with the environment. Both medical diagnosis and situation recognition are regarded as operating on data which have already been refined and operated upon by humans. In the early days of pattern recognition research, it was intuitively recognized that duplicating human classification performance with raw data posed very difficult problems which would not be present in classification tasks based on data refined by human preprocessing. The latter problem has come to be studied separately under such titles as *decision making*, or more accurately, *predecisional information processing*. The term *pattern recognition* has thus been reserved for problems in which raw data are to be classified.

If we consider raw data as the starting point for pattern recognition, I believe we can identify three key steps in which useful contrasts and comparisons may be made between human and machine processes. These are: 1) selection of data sets from the raw data; 2) selection of a useful set of features in terms of which the raw data can be described; and 3) the use of these features in a decision process to classify the data sets. Let us consider each of these in more detail.

1. The selection of data sets is a process which humans accomplish so easily that we can scarcely conceive of it as a problem. We can look at a photograph and

spontaneously pick out regions which represent individual things. This process, long known in psychology as the figure-ground phenomenon, seems to be one of the most difficult tasks for machine pattern recognition. Many of the cases in which automatic pattern recognition appears to be making its best progress are cases in which the problem of figure-ground distinction is minimized. Hand-printed letters, for example, provide a clear indication of what area consitutes a single thing, because each letter is separated from the others by white space. Similarly, in photo-interpretation, the identification of terrain classes or clouds promises to be simpler than the identification of objects, in part because with terrain classes or clouds an entire frame can usually be treated as a single thing.

2. The selection of a useful set of features is probably one of the most important problems remaining to be solved in automatic pattern recognition. In this matter also, the human recognition system seems to be much more powerful than automatic systems, at least when it is working with data from a familiar domain, such as visual imagery. The appropriate set of features apparently depends upon a number of conditions, including the source of the data, the characteristics of the transducers and the identity classes relevant to a particular task. Machine pattern recognition has been achieved by selecting features for rather specific circumstances. These circumstances, however, may be so specific as to greatly restrict the usefulness of the machine processes.

Humans, on the other hand, are extremely flexible with respect to the circumstances under which they can recognize patterns. This facility could result from a more generally useful set of features than the developers of automatic pattern recognition processes have yet discovered. There is, however, another possibility which may deserve more attention than it has so far received. Humans may also select the appropriate feature set for each specific circumstance, but on the basis of the data derived from that specific circumstance. Such selection has been explored in machine pattern recognition under the title, "unsupervised' or "automotous" pattern recognition. An automatic system based on unsupervised processes would not have to be provided with a preselected set of features. Instead, it would select features out of each particular collection of patterns presented to it for recognition.

The unsupervised selection of features is theoretically possible when certain conditions are met (Cooper 1964; Evans, 1964). Furthermore, our research has shown that when these conditions are met, humans do exhibit unsupervised

feature selection. This technique, therefore, may be one of the methods by which human pattern recognition achieves its power. If so, such a technique might offer important contributions to automatic pattern recognition.

3. The third step, the application of decision processes, is a problem which is more familiar and better understood. At this point, the raw data have been reduced and refined by transforming them into descriptions in terms of features. The problem then becomes a particular case of the general problem of classification, quite like the problem of medical diagnosis and situation recognition.

The general classification problem has been rather extensively studied mathematically, and a number of good decision models exist. While human processes of this kind are still not adequately understood, I would venture to suggest that for well defined classification problems, the mathematical models are already superior to human processes. Obviously, not all problems are well defined, or there would be more automation in diagnosis and situation recognition. But it seems unlikely that progress in automatic pattern recognition is being impeded by a lack of adequate classification models.

In closing let me suggest the kinds of benefits I see from a joint study of human and automatic pattern recognition. Automatic pattern recognition first offers a definition of the problem - it is very difficult for people who look at the world through the mechanisms of a powerful built-in pattern recognition system to grasp the difficulties in extracting classifications from raw data. A decade of efforts to automate the process, however, has demonstrated the difficulties quite clearly.

Automatic pattern recognition also offers a conceptual framework and, in the last stage of the process, some good mathematical models. Both of these can surely be applied fruitfully to the study of human pattern recognition.

On the other hand, the most immediate problem now confronting automatic pattern recognition appears to be feature selection. Humans evidently have feature selection techniques which are well suited to our environment. Such techniques have been selected through millions of years of evolution and - for each individual - through several decades of experience. These techniques, if they can be identified and described precisely, may be of significant value for automatic pattern recognition.

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GRAPHICAL DATA PROCESSING

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INTRODUCTION

Advanced planning studies conducted at USAECOM in the fifties indicated that as a result of the rapid advances then being made in computer technology a problem area would soon exist requiring faster methods for data entry. The data entry problem referred to here is not that of reading data into the computer from cards and tape, but rather the problem of reducing the time required to filter and format data from "real-world" environments to a form suitable for direct application to the computer.

It was realized in an early phase of the data entry study, particularly when considering the automatic transducing of data from "real-world" environments directly to the computer, that the basic problem requiring solution was that of pattern recognition. Closely associated with the pattern recognition requirement is that of data filtering. In fact, in many applications the recognition and filtering functions are so closely associated that it becomes difficult to isolate them. However, from a practical standpoint of machine design it is sometimes possible to perform these operations in tandem where data filtering is performed first. This technique minimizes the amount of extraneous information that the recognition section of the machine is required to handle.

The recognition problem, when considering information contained in "real-world" situations, is complicated by the large volume of data that must be handled, and the incompatibility existing between the variant characteristics of "real-world" situations and the constrained input requirements of the Automatic Data Processing (ADP) system. Because of the large number of data bits per field of information that must be filtered and processed, and because of the real time processing requirement, extracting data by serial bit scanning was considered to slow. As a result, efforts have been directed in the area of parallel filtering of the input data. Also, the variant characteristics of the pertinent data to be extracted, and the fact that these data are usually embedded in a complex background, seriously limited the practicality of using "template matching" techniques to effect pattern recognition. This latter limitation led to the consideration of adaptive-learning techniques for pattern recognition.

One of the reasons that adaptive-learning procedures are useful for effecting pattern recognition in "real-time" is that they do not require the use of previously prepared programs for decision; using instead, adaptive networks that can be modified automatically in the initial training mode so that they are statistically weighted in accordance with data contained in the training set. These weighted networks are then

used in the operational mode to effect data classifications, each of these categories being assigned an appropriate electrical code consistent with machine language requirements.

A discussion of processing real-time problems by use of parallel input data filtering followed by adaptive-learning techniques for recognition is presented. The discussion focuses on a description of USAECOM's adaptive-learning/digital computer complex known as MINOS III. This machine represents the first integration of a full size adaptive-learning machine and a conventional digital computer. The combination provides a powerful tool capable of performing several levels of operation and control that is not available when the machines are used singly. These functions include independent operation of the adaptive-learning machine and the digital computer, and integrated operation. The preparation of data, and its applications and processing on MINOS III is described. To illustrate the variety of problems MINOS III is capable of handling examples are presented involving the automatic processing of (1) hand-printed map symbols, (2) pictorial classification of military tanks, (3) waveform classification, and (4) automatic reading of topographical information from military maps.

SYSTEM ORGANIZATION

MINOS III is organized in two parallel branches each capable of independent operation. This is illustrated in Fig. 1 where one branch is shown consisting of a Scientific Data System's digital computer (SDS 910), and the other branch comprises the adaptive learning machine. Provisions are also available for interconnecting the two systems thereby enhancing their individual operational capabilities. It is also possible to operate the two systems in series by using the adaptive-learning section as an interface between real-world happenings and the coded input requirements of the digital computer. This series system type of operation can be extended to that of a closed loop thus establishing an adaptive-learning/digital computer feedback system. The availability of feedback techniques within the MINOS III complex opens up new possibilities for on-line solution of problems requiring search, locate, identify, classify, track and predict. Operational details of theses capabilities will be illustrated with examples later.

The digital computer section of MINOS III is a commercial SDS 910 possessing 12,288 words of core memory. Periphery equipments are: teletyper/paper tape set, paper tape reader, paper tape spooler, magnetic tape unit and flexowriter. Several specially written programs have been developed for graphical data processing using integrated operation of the adaptive-learning machine.

The adaptive-learning section of MINOS III is organized as illustrated in Fig. 2 and consists of the following units: an optical preprocessor, for use in filtering the raw input data; an adaptive unit, for providing statistical established logic; an output display, for supplying visual indications and electrical output codes; and a training and comparator

unit, for use in adjusting the statistics of the adaptive portion of the machine. The function of the preprocessor is to reduce the raw data to manageable proportions thus simplifying the decision making requirements of the adaptive portion of the machine. In the adaptive-learning section of MINOS III all pertinent input data are reduced in the preprocessor to 100-bit words. The adaptive unit is desinged to accept 100-bit words and make appropriate classifications using a 9-bit output code.

Two nonconcurrent phases of operation are provided; the training phase and the classifying phase, which is the period when the machine is producing useful output. During the training phase data representative of the desired categories of classification are fed into the machine. The training algorithm of the machine then effects appropriate weight adjustments in the adaptive unit until a match is obtained between assigned and generated codes as indicated by the comparator unit. The matched condition denotes that the machine has converged, and the data are correctly identified. This process is then repeated until convergence is obtained on all training data for which condition the machine is said to be trained and is ready to accept unidentified data for category classification.

PREPROCESSOR

A special electro-optical preprocessor (1) has been developed for forward operation of the adaptive unit. The electro-optical preprocessor operates in the parallel mode as an image feature extractor and filter. Functional diagram of the optical preprocessor is shown in Fig. 3. The basic function performed by the preprocessor is that of transforming the original input data, which is in optical form, into a set of electrical signals appropriate for application to the adaptive section of the machine. Referring to Fig. 3, the input data to the system are in the form of 35 mm glass slides. The pattern on the slide is replicated 1024 times by the 32 x 32 lens array that is illuminated by parallel light from the condensing lens. Each of the 1024 replicated images produced by the lens array lie in a plane that coincides with the position of the emulsion layer of the photographic plate. This plate carries 1024 masks, one for each image, each of which acts as a separate feature filter by virtue of its geometric configuration of opaque and transparent pattern areas.

Figure 4 illustrates the use of area type masks for image feature extraction. A photocell is dedicated to each image/mask combination, and its output is an analog signal proportional to the integral of the light transmitted by its associated mask. An array of 100 area type masks are shown in Fig. 5. Each of these masks possess a 50% transparent area. Area type masks are inclined to be very sensitive to average brightness of the image field being processed. This characteristic is not particular detrimental to use on line drawing such as military map symbols, but can produce large errors when processing pictorial information, which frequently have large variations in average light intensity.

Another type of mask studied is that dedicated to detection of image edges. An edge represents a minimal amount of preprocessing by the mask, and is a feature second in simplicity only to a spot. Physiological studies have indicated that edge detectors play a significant role in visual perception. The edge mask design is also based on the assumption that the working region of each mask pair should be "local" rather than "global" as were the area type masks. This feature shows improved signal-to-noise ratio at the cost of somewhat reduced translation-independence. In other words, each mask pair will have the task of recognizing only local features of the pattern, but recognizing these more reliably. The local masks can also be made to act as feature detectors that carry gross positional information. The differential nature of the mask pair has the additional advantage that they are substantially insensitive to the overall brightness level, this is in contrast with the area type mask.

The operational technique of an edge detection mask pair is illustrated in Fig. 6. It should be noted that there are 511 similar masks pairs each with different rotations and translations. If we assume that the black areas representing the masks are transparent, then it can be seen that the top mask in the illustration will not pass light because of its orientation with respect to the opaque triangle, while the bottom mask will transmit light. This light will activate the lower photocell and produce a binary signal at the output of the quantizer. If both masks had coincidedwith equal light intensity backgrounds, the outputs of the photocells would have cancelled resulting in no quantizer output. A slight bias is provided in the subtraction of the signals generated by the masks so that if the outputs of the mask pairs are equal the binary output is "off". To determine edge orientations, one mask of each pair is designated as "positive", the other "negative". The orientation of the mask pair is then named according to the direction of the vector drawn from the negative mask to the positive mask. If this vector is vertically upward, it is called a "north" mask, if it is vertically downward a "south" mask. Other mask orientations occur for each 30° of circle. Each of these 12 different mask orientations are distributed over the mask plate. For example, there are 45 north-south mask pairs equally distributed over the mask plate. The complete mask plate is shown in Fig. 7. Referring to Fig. 7 it will be noted that in addition to the simple edge detection mask pair shown in Fig. 6, there are other configurations in the forms of squares, rectangles, triangles, and combs. These represent special purpose mask pairs for use in studying automatic centering techniques when operating in a free-field of data.

It should be noted that a meaningful rationale is needed in the data reduction technique required to transform output data from the 512 edge detection mask pairs to the 100-bit output of the preprocessor. This problem was resolved by dividing the mask plate into nine equal areas and connecting all mask pairs of a given orientation in the same area to a common "OR" circuit. For example, there are 45 edge detection mask pairs with a "north" orientation, which gives 5 edge detection mask pairs per divided area. These five mask pairs are connected to a common

"OR" circuit. If one or more of these edge detection mask pairs are activated an "ON" condition would exist for this particular "OR" circuit. This "OR" circuit output is assigned to the number one bit position of the 100-bit word. Likewise the rest of edge mask orientations are assigned the remaining 99 bits. By using the computer to analyze the output of the 100-bit words from the preprocessor, it is possible to determine areas of edge activity and to automatically select and magnify these areas of interest. This feature is particularly advantageous when operating in a free-field containing several isolated patterns.

ADAPTIVE UNIT

The basic unit of the adaptive-learning section of MINOS III is the threshold logic unit (TLU) shown in Fig. 8. A simple physical interpretation of the TLU is that it constitutes a test by computing a weighted sum,

$$y_j = \sum_{1}^{d} x_i w_{ij} \tag{1}$$

which is an analog value. Inputs to the TLU's are the pattern components under test,

$$x_i = (x_1, x_2, x_3, \ldots x_d) \tag{2}$$

In the example under discussion these pattern components are the 100-bit output from the preprocessor. The pattern components are multiplied by the weighting factors established during training,

$$w_{ij} = (w_{1j}, w_{2j}, w_{3j}, \ldots w_{dj}) \tag{3}$$

where $j = 1, 2, 3, \ldots, d$
Since Eq. 1 is the dot product of the pattern components, it is frequently referred to as a dot-product unit (2). In certain applications where the TLU is required to make a yes-no classification of its input data, it is operated with a threshold. For this application, if the sum of the inputs is greater than are arbitrarily assigned threshold, generally zero, $y_j = +1$, if the input sum is less than zero, $y_j = -1$.

To make statistically significant decisions more than the yes-no output of a single TLU is required. The problem of organizing TLU's in networks that are capable of statistically significant decisions has been extensively studied. Clues have been sought in anatomy and physiology studies of that portion of our brains involved in higher mental activity. These studies,, however, have failed to uncover a preferred network organization, so the objective continues to be pursued. In the interim various network configurations are being tested. The adaptive-learning section of MINOS III incorporates a network organization known as a "committee",

An adaptive unit organised with a "committee" structure is shown in simplified form in Fig. 9. Numbers associated with the adaptive unit represent typical values used in MINOS III. The committee machine bases its classification on the majority vote of an odd number of trainable TLU's. There are 9 committee type TLU's each having 7 voting inputs. The threshold of each votetaker is adjusted so that an output of +1 is obtained if 4 or more inputs are +1, otherwise the output is zero. The power of the committee machine resides in the fact that not all of the TLU's need give the correct classification. It is only necessary that the majority voting be correct in order to obtain the correct output code. The difficulty that unfortunately accompanies the committee machine is that it requires a rather complex training logic.

Each of the 6300 trainable weights in the input lines to the 63 TLU's are of the analog type providing approximately ±100 levels of storage. It is the analog storage level of these weights that is adjusted during the machine's training phase. The value of the weights thus established being used to effect data classification during the machine's operational phase.

TRAINING

The statistical logic used for decision-making is established from the training set data. It is, therefore, important that the training set data be representative of the raw data that is to be classified. It is also important that the training set data be sufficiently large. No direct figures can be quoted as to the exact specifications of the training set data as this will vary with the type and degree of difficulty associated with the problem in question. The preparation of the training data requires that each pattern be identified by some form of marking according to a conveniently assigned code. The training patterns may be presented to the machine in any sequence. At the start of the training cycle all weights in the adaptive unit are set to approximately zero. When the first training pattern is exposed to the machine an arbitrary output code will be indicated, which generally differs from the assigned code. This difference in codes will automatically cause the machine to go into the learning cycle. During the learning cycle selected weights are adjusted until the correct output code is indicated. The machine then automatically proceeds to learn the correct identity of the next pattern and so on until the complete set of patterns are correctly identified. This can require several passes through the training data set as learning adjustments of the weights are not completely independent.

The training algorithm built into the adaptive-learning section of MINOS III operates as follows: The assigned and indicated codes are compared in the comparator unit, Fig. 2, and if they are different the learning cycle is automatically initiated. First the output bits in error are identified and then a procedure is inititated to correct these errors. Suppose the top output bit as shown in Fig. 9 is the only bit in error. The next sequence will be to determine which of the 7 input

voters are in error. If we assume that 4 of the voters are incorrect it will be necessary to change the vote of at least one. The machine's algorithm operates to always change a minimum number of voters and to change those voters requiring a minimum of weight change, therefore, all weights associated with the incorrectly voting TLU will be incremented. This means that those weights connected to the +1 inputs are altered in a direction opposite to that of the weights connected to the -1 inputs. The size of the increments is the same for all weights and the size and direction is determined by the total change needed in the analog sum to effect a reversal of the associated TLU. When the TLU vote has been changed the machine will recognize the correction and proceed to automatically select the next pattern and repeat the learning cycle. After the machine has converged to the correct identification of all members of the training data set the training cycle is terminated and the machine is ready to receive data for classification.

It should be noted that the training period proceeds the utilization period. The committee structure has proven very effective where training and utilization periods remain isolated. In the committee type machine the degree of difficulty of problem solution is frequently related to the output code. As this code is arbitrarily assigned during the training phase it is possible to increase the difficulty of the problem by an unfortunate code choice. The reason for this lies in the nature of the committee structure and its training algorithm, which effects rather drastic statistical changes on previously trained conditions.

APPLICATIONS

It has been stated that the computer is an amorphous instrument lacking determinate form until supplied with a program and/or training set, the type of program and/or training set being related to the problem under consideration and its adaptability to the machine. This interrelationship between problem, machine and method of processing gives considerable latitude to operational procedures and will be described by illustrative examples.

The first application of MINOS III to be discussed relates to the subject material of military map symbols. These tests were made for the following purposes: to determine the proficiency for automatic recognition and classification of military map symbols (both by parallel operating adaptive-learning and its computer simulation), to provide a standard against which to evaluate the adaptive-learning machine performance, and to investigate the effects of specific machine imperfections. This latter problem is compounded because of the adaptive characteristics of the machine, which on relatively simple problems uses its surplus capacity to "train around" defective operations. This puts a severe limitation on legitimate inference and hence diagnosis when running problems that are "difficult".

Types of military map symbols used in these tests are illustrated in Fig. 10. Test sample material was generated by asking forty-five people

to draw a set of these nine map symbols on individual 2 x 2 inch glass projector slides. In drawing the slides, they were instructed to avoid major translations and rotations of the prototype figures, but also to avoid slavish copying of the figures. A small paint brush and opaque fluid were used. The resultant slides show deformations associated with hand-drawn figures as indicated in Fig. 11.

The generation of training and testing sets is illustrated in block diagram Fig. 12. The data base of 405 slides was separated into two groups, one consisting of 324 slides for use in training, and the other group consisting of 81 slides for use in testing. Each slide was shown in ten different positions to the preprocessor thus producing 3240 patterns for training and 810 patterns for testing.

Using the above data set the adaptive-learning section of MINOS III trained to 1% error in 17 iterations. During the testing phase of the operation the adaptive-learning section made 10% error, while the simulation made 8% error. It is noted that the error rates for the test data are higher than for the corresponding training data. These differences reflect the inability of thirty-six training slides in each category to represent the full category, suggesting that the patterns in error are beyond the scope of the training patterns.

The second application of MINOS III to be discussed pertained to using a 100-element optical preprocessor with mask plate illustrated in Fig. 5, in conjunction with the adaptive-learning section of the machine. This test was to determine the ability to classify photographic objects in a naturally occurring noisy background. The materials used were aerial photographs of tanks and the subject matter was presented to the preprocessor in the form of 35 mm slides. A training set of 50 photographs was selected of which 25 contained tanks. On training the system converged to the correct classification of tanks and no tanks after 25 iterations.

Thirty-four different photographs were then presented to the machine for identification, there being 15 examples of no tanks, and 19 examples of tanks. Of the 19 tanks 18 were correctly identified. Of the 15 no tank slides, 14 slides were correctly identified. The one no tank slide definitely indicating a tank is shown in the lower right-hand corner of Fig. 13. On close inspection of this photograph it was found that a rectangular building was present, which a human observer might also have mistaken for a tank. The upper left hand photograph is typical of the tanks pictures, while the remaining two photographs are typical of the no tank photographs.

The third application is that of waveform classification. It is frequently of military importance to classify waveforms into meanful categories. These waveforms may have origin ted in any of the physical domains; such as, sound, mechanical shock, light and rf radiation, or as the compilation of general statistics. In the application under consideration a test set of 80 waveforms were used. Each of these waveforms

consisted of 10 independent points, which were obtained from a random table of digits. The test set can be considered as consisting of 80, 10-dimensional vectors where for illustrative purposes only 24 are shown in Fig. 14.

The function performed by MINOS III was to classify each group of three of these waveforms into a different category as indicated in Fig. 14. This was readily done without error for the illustrated noise free waveforms. When noise was added corresponding to an rms signal-to-noise ratio of 11.4, 2% error was experienced after 4 iterations of training. When the rms signal-to-noise ratio was reduced to 3.8, the error rate increased to 12% after 26 iterations of training.

Classification problems of the type illustrated in Fig. 14 involve multi-dimensional data and are typical of the more difficult pattern recognition problems where no single pattern is representative of the pattern in the same category. Such types of problems deal with multi-modal distributions in contrast to the more simpler unimodal distributions where the mean vector for a given category can be viewed as a typical or prototype pattern for that category, the other patterns being merely noisy versions of that ideal pattern. Multimodal distributions do not readily yield to computational procedures as no theory comparable to that for unimodal distributions exists. Since the operation of MINOS III does not depend on the existence of prototype patterns representating each category, (no exact pattern-to-pattern correspondence is required) the way it is trained on patterns having multimodal distributions is no different from the way it is trained on patterns having unimodal distributions. This is the outstanding advantage of utilizing adaptive learning machines, such as MINOS III in the solution of problems involving multimodal distributions.

In the fourth application consideration has been given to the possibility of using techniques, such as available from MINOS III, to automatically extract elevation data from military maps through the process of contour line identification. Two distinctly different classes of methods, scanning and lookup, have been considered for reading of the elevation data from military maps by MINOS III techniques. Using scanning methods, when a point on a map is specified, the map-reading system explores the map in the vicinity of that point, interpolates between appropriate contour lines, and computes the elevation for the point.. With lookup methods the elevation is obtained by one of a number of possible table lookup methods, the table having been obtained from the map data previous time. The table would be generated off-line by automatic scanning.

Detailed steps for automatic reading of elevation data from military maps has been proposed by Duda and Hart (3). The method uses electronic scanning and character recognition. Basically, the idea is to go out from the specific point on the map until an index contour is located, follow that contour to find the printed contour elevation, read and recognize the numbers, go back to the specified point, note the number of intermediate contours crossed, and interpolate to compute the desired

elevation. The actual algorithm is more complicated, of course, because it must determine whether one is going uphill or downhill across contour lines, and whether or not the same line has been crossed twice. The important point here is that the map reader must be able to distinguish between different types of contour lines, follow a contour line, read and recognize numerals and follow a logical sequence of operations.

While MINOS III has not been used directly to automatically read elevation contours, all the proposed functions required to effect the readings have been demonstrated on an experimental basis using MINOS III. Also, it should be noted that a very large memory would be required to store the extracted elevation data.

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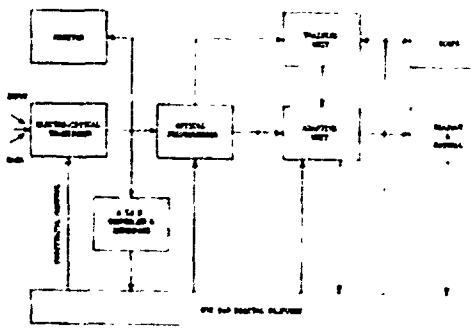

Fig. 1. MINOS II System

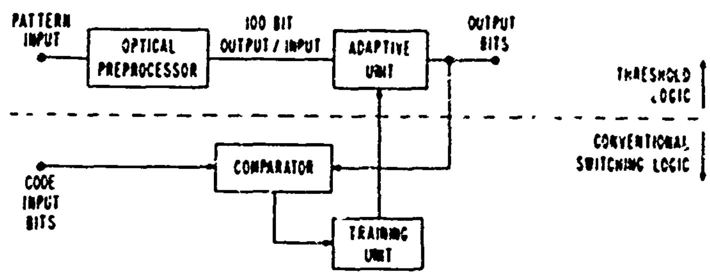

Fig. 2. Adaptive-learning Organization

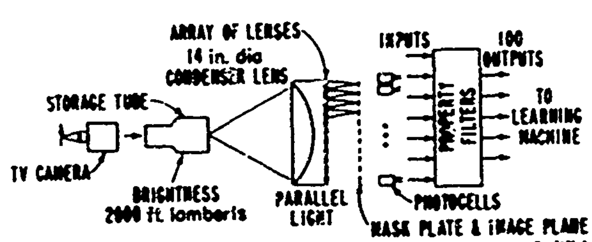

Fig. 3. Functional Diagram of Optical Preprocessor

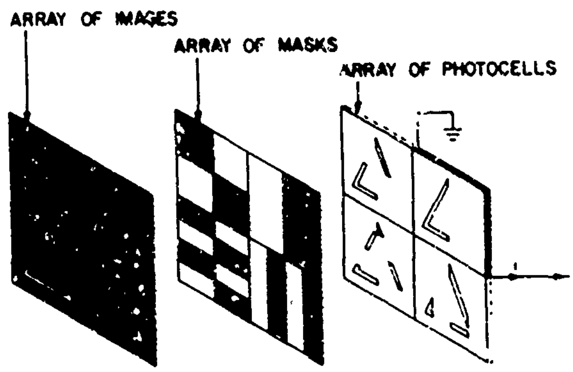

Fig. 4. Sampling By Multiple Images And Masks

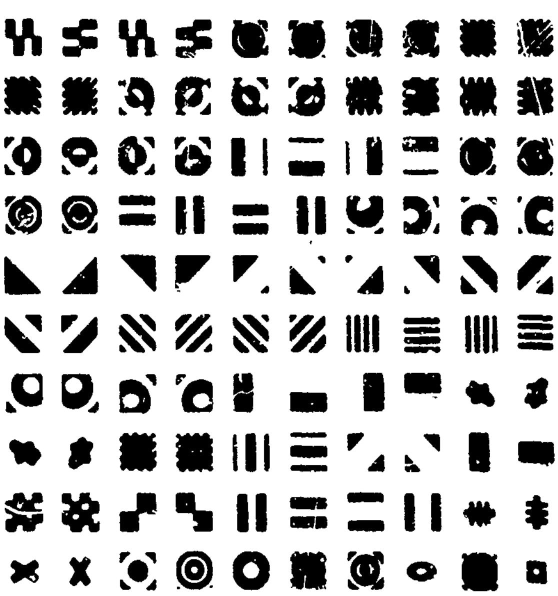

Fig. 5. 100-Element Mask Plate

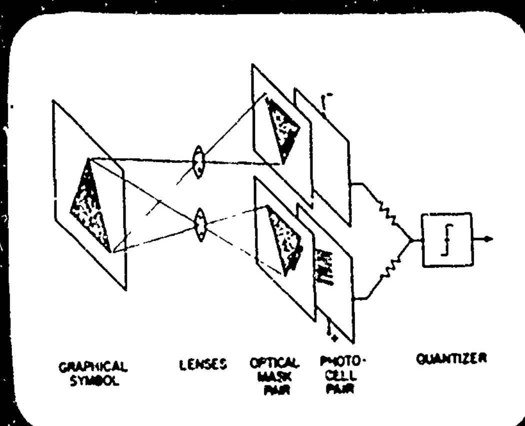

Fig. 6. Edge Detection Masks

Fig. 7. Edge Detection Mask Plate

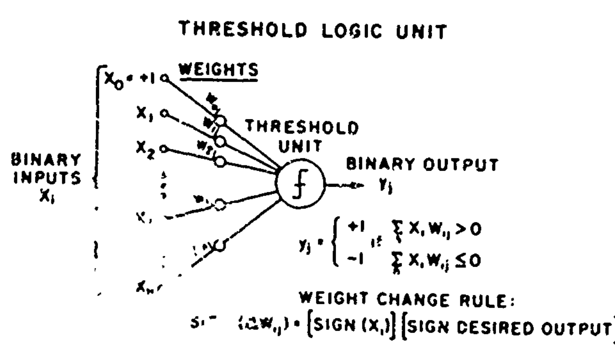

Figure 8.

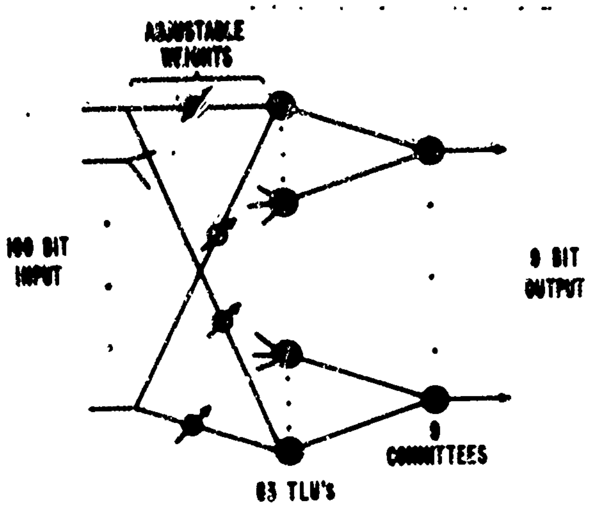

Figure 9. ADAPTIVE UNIT

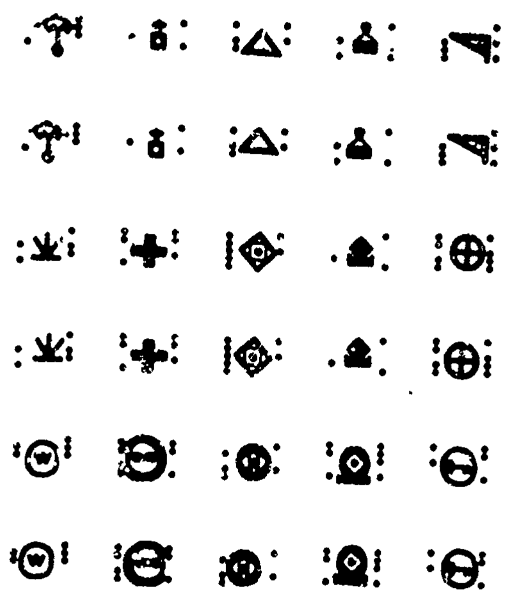

Fig. 10. Military Map Symbols

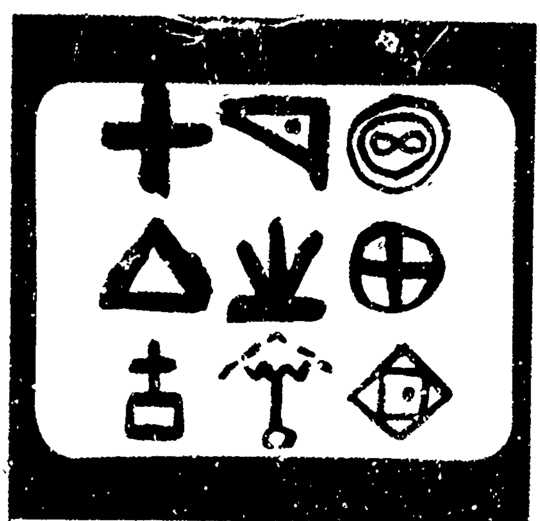

Fig. 11. Hand-drawn Map Symbols

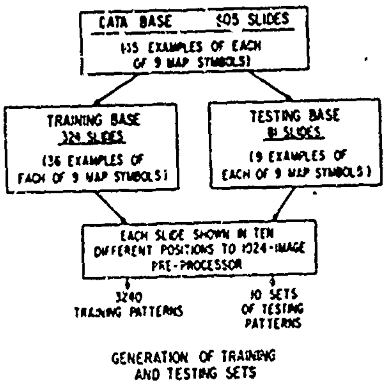

Fig. 12. Data Set

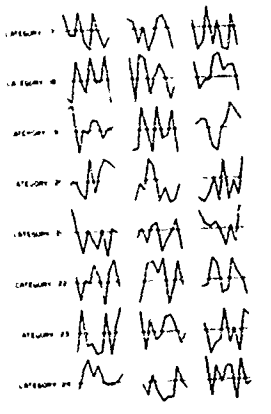

Fig. 14. Waveform Samples

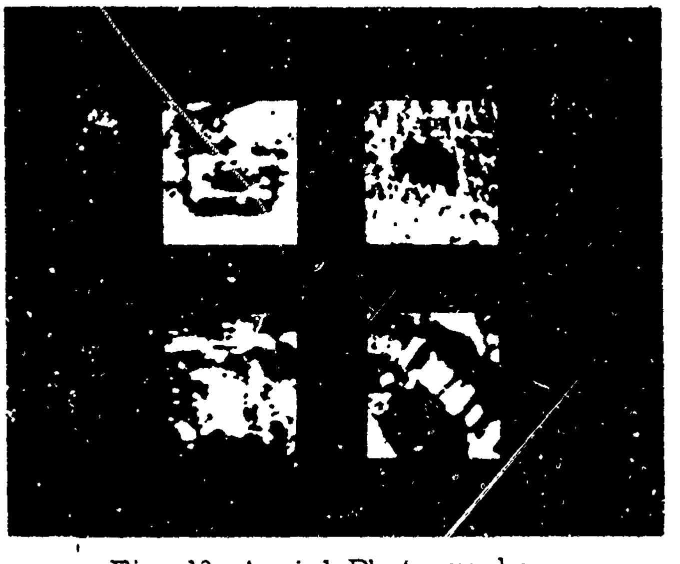

Fig. 13. Aerial Photographs

MODELING THE PATTERN RECOGNITION ENVIRONMENT

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In the study of any pattern recognition process, there are two components: a pattern recognizer and its environment. By environment I mean batches of data, visual imagery, or whatever it is that is input to the pattern recognizer. Just as a radio receiver must be tuned to the wave band of the signal it is to receive, the pattern recognizer must be attuned to the relevant characteristics of its environment. The relevant characteristics, of course, are those which differentiate between patterns belonging to different classes and fail to differentiate between patterns of the same class.

Because of the close relationship between pattern recognizers and environment, knowledge about one is to some extent knowledge about the other. Thus if we know the relevant characteristics of some envionment, we are in a very good position to design a pattern recognizer for it. Conversely, if we have a pattern recognizer suitable for a given environment, and if we know the details of its processes, we can draw inferences about the relevant characteristics of the environment.

From this viewpoint, there is a complementary relationship between the study of automatic pattern recognition and that of human pattern recognition. Human pattern recognition is a process about which little is known. In order to study it, we create a controlled (therefore, known) laboratory environment. Any automatic pattern recognition process is known (or subject to being known) in complete detail. It is likely to be studied in an environment composed of real world patterns, an environment about which relatively little is known.

Thus in the human case we have an unknown process in a known environment and in the automatic case, a known process in an unknown environment. Both arrangements reflect the judgment that at least one of the components, the recognizer or the environment, must be known. The importance of a known and controlled environment has long been recognized in the study of human pattern recognition. What has not been so generally recognized is that if laboratory results are to apply to the natural environment, the results must be obtained with an environment which models, in appropriate

respects, real world patterns. This need has been noted by Brunswik (1956), and by Attneave and Arnoult (1956), but serious efforts to model real world patterns could not be undertaken without some knowledge of their relevant characteristics.

It is in identifying the relevant characteristics of the environment that the study of automatic pattern recognition makes a major contribution to the study of human pattern recognition. It may seem strange to suggest that an automatic pattern recognizer can tell us something about the environment that we cannot discover with our own built-in recognition systems. But our built-in systems obscure, rather than elucidate, the environmental characteristics relevant to pattern recognition. We see the world through our built-in systems, and pattern recognition seems so simple and obvious as to pose no problem at all. No doubt this apparent simplicity contributed to the early optimism regarding development of automatic pattern recognizers. Ten years of effort in this direction have served to demonstrate that pattern recognition is in general quite difficult. That information is something we could never have learned from our senses.

The efforts to develop automatic pattern recognizers have also provided a description of the world in terms of raw data, as the world appears to the artificial retina of an image scanning device or to the receptors on the human retina. These efforts have thus provided a basis for creating model environments which reflect some of the characteristics which have been found relevant to pattern recognition in the natural environment. This paper describes several such models developed in our laboratory.

A model is not intended to be a complete duplicate of the real thing. It is intended to reflect those aspects of the real thing which are considered important for some objective. The efforts reported here were intended to incorporate into the models the characteristics shown to be important by research in automatic pattern recognition, while retaining the kinds of environmental control necessary for replication and generalization of experimental results. All of these systems incorporate the fundamental characteristics necessary to constitute a pattern recognition task: There is a collection of things and a small number of classes to which the things "belong". There is a set of relevant features which covary with the classes so that these features could be used to assign things to classes with near perfect accuracy. No single relevant feature, however, is perfectly reliable; moreover, there are many

other features which are irrelevant. Thus members of the same class are in general not identical.

Modeling The Data Recognition Environment

Many kinds of data present values on one variable as a function of another variable, and people often find it useful to represent such data visually in the form of bar graphs (histograms) or line graphs. We have developed two systems, Vargus 7 and Vargus 9, for creating pattern classes in artificial data of this type. The systems differ with respect to the relevant features, but both systems allow control over such things as the amount of within class variability and the magnitude of differences between classes.

The Vargus 7 system produces data as illustrated in Figure 1. The system is based on a Markov process which generates a sequence of numbers. These numbers are then plotted in sequence as column heights to produce histograms. The line graphs are produced by replacing the columns with points marking the column tops and then joining the points with straight lines.

The relevant features in the Vargus 7 system are particular sequences of numbers favored by the Markov process. These features appear in the graphic plots as particular configurations of column heights or lines. By use of the theory of Markov processes, it is possible to manipulate these features while controlling, or independently manipulating, the information content and the extent to which individual plots adhere to the class characteristics. A number of other things can also be controlled in this way (Evans, 1967). The features introduced by the Vargus 7 are independent of location and so must be identified solely on the basis of configuration. In this they are analogous to transients in a time series.

The Vargus 9 system produces patterns as illustrated in Figure 2. This system also generates a sequence of numbers, from which plots are produced just as with the Vargus 7. In the Vargus 9 system, however, the features are strictly place dependent. Each column location in the plot is individually assigned an average height. This collection of average heights constitutes the set of characteristics associated with a pattern class. Different classes are distinguished in general by different average heights in each column.

Individual instances are produced by adding to each

average height a quantity which is analogous to an error of observation. This quantity is a random variable unimodally and symetrically distributed about zero, and it is independently determined for each column in each instance, as would be appropriate for an error of observation. This error term does not alter the average height of a given column across the population of stimuli, but it does introduce variability. The variability in turn can be manipulated independently of the class-defining characteristics. This system is described in more detail elsewhere (Evans and Mueller, 1967).

Place dependent features, such as are modeled by the Vargus 9 system are found in many contexts: personality profiles, aptitude profiles, economic indices, spectral analysis plots, etc.

Modeling the Image Recognition Environment

Although the above systems are models for pattern recognition environments of interest, the systems are too simple and abstract to be representative of visual imagery. In the generation systems to be discussed in this section, we have sought to develop a spectrum of model environments. All of these incorporate some features which might be found in real world images, but their products range from simple and unfamiliar closed curves to things which clearly resemble images in practical identification tasks.

The Vargus 10 system produces stimuli such as are illustrated in Figure 3. These stimuli are all closed outlines and are in general unfamiliar. They are constructed of components, however, which appear in familiar figures. The components (such as loops, angles, curves, and straight lines) were obtained from figures drawn by a commercial artist. The figures were drawn in such a way that they could be readily decomposed into components which could in turn be fitted together in many different ways. The Vargus 10 system constructs patterns by choosing a random sample from the set of components and assembling the chosen sample into a closed figure.

The motivation behind the development of the system lies in two assumptions: first, that the human pattern recognition system is adapted particularly for the recognition of patterns which actually occur frequently in our environment, and second, that this adaptation depends in part upon analyzing the patterns into commonly occurring components. This system allows us to introduce such components into studies of recognition performance and thereby investigate their effects.

The Vargus 11 system provides a very flexible method by which non-identical figures representing a pattern class can be produced for both unfamiliar figures, such as those generated by the Vargus 10, and for familiar figures such as might be produced by an artist. The Vargus 11 system simulates the sketching behavior of a human. It accepts a prototype matrix which determines the general shape of the pattern to be drawn. The system then draws a path through an output matrix much as a human would draw a contour with a pencil. Various subsystems control aspects of the generation process, such as symmetry, straightness of lines, and variability about the prototype. Examples of the Vargus 11 patterns are presented in Figures 4, 5, and 6. Figure 4 presents several sketches produced from an unfamiliar prototype generated by the Vargus 10 system. Figure 5 presents several sketches produced from familiar prototypes.

Figure 6 illustrates the construction of complex patterns by means of the basic Vargus 11 system and a supplementary program. In this case, the process began with a sketch of a tank adapted from a sketch provided by Dr. Marshall Narva of Behavioral Science Research Laboratory. In the adaptation, a number of details were omitted and the tank was decomposed into gun barrel, turret, and body. Separate prototypes were then prepared for each of these components, and the Vargus 11 system sketched examples of each component. Finally, the tank was assembled by combining three matrices, each containing one component sketched in the appropriate place. The results of the successive incorporation of components are illustrated step by step in Figure 6.

Conclusion

The environmental models presented here represent a methodology, a set of tools. It is difficult to talk about tools without talking also about what is to be done with them.

The general purpose of these models is to permit the measurement of human performance in pattern recognition tasks as a function of variables indicated to be relevant in real world pattern recognition problems. A number of studies toward this end have been conducted in this laboratory and elsewhere. Others are in progress or preparation. From such studies, we expect to obtain a detailed description of critical aspects of human pattern recognition, a description which will later form the basis for quantitative models of this behavior.

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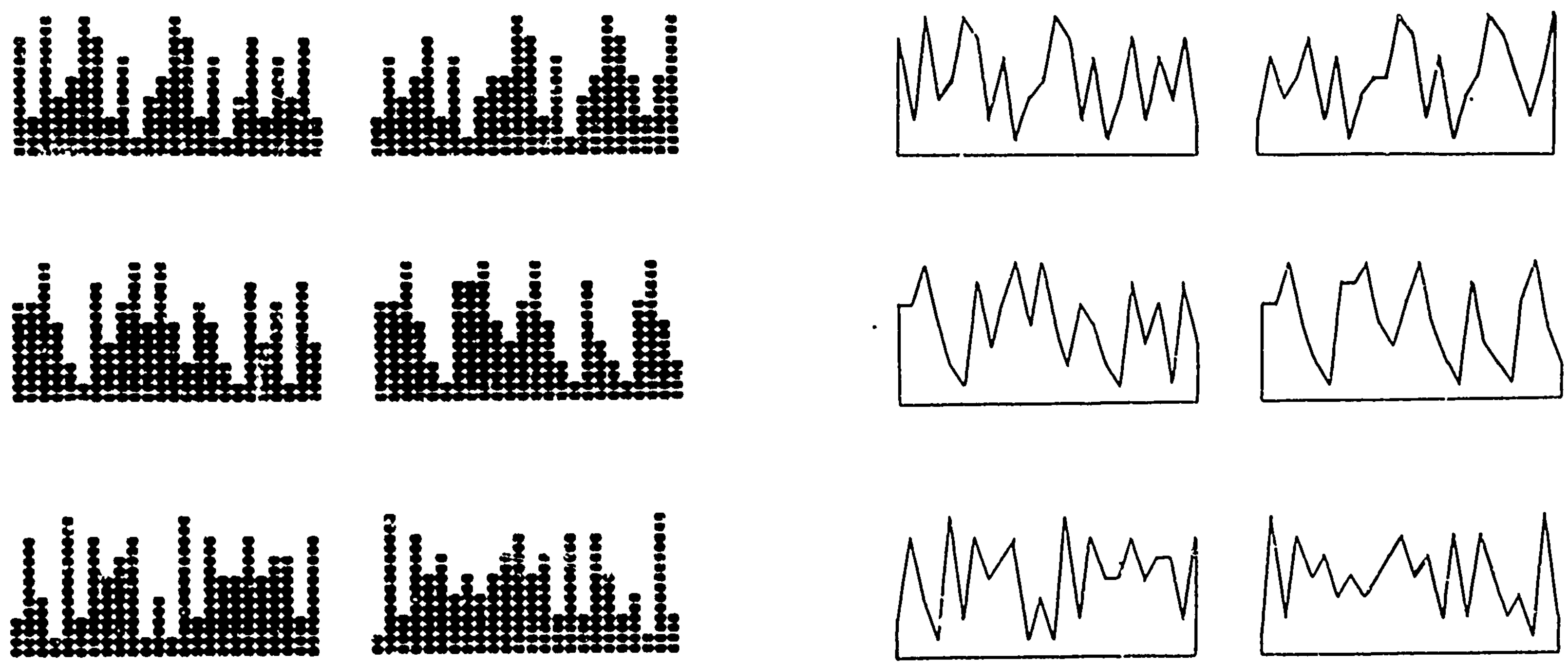

Fig. 1. Examples of Vargus 7 patterns in both histogram and line graph modes of representation. Each row represents a different pattern class.

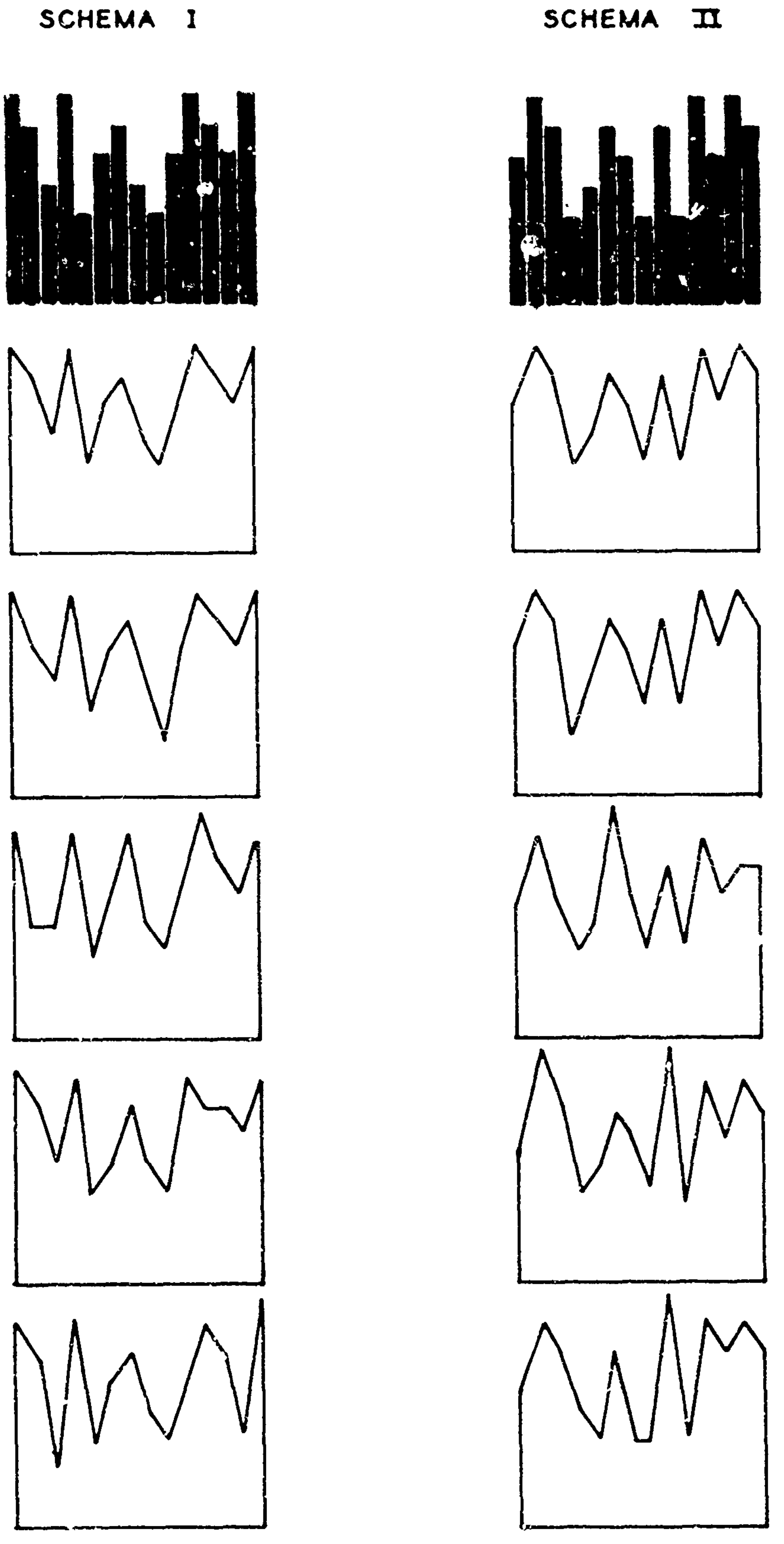

Fig. 2. Examples of Vargus 9 patterns in histogram and line graph form. All patterns in the same column belong to the same pattern class.

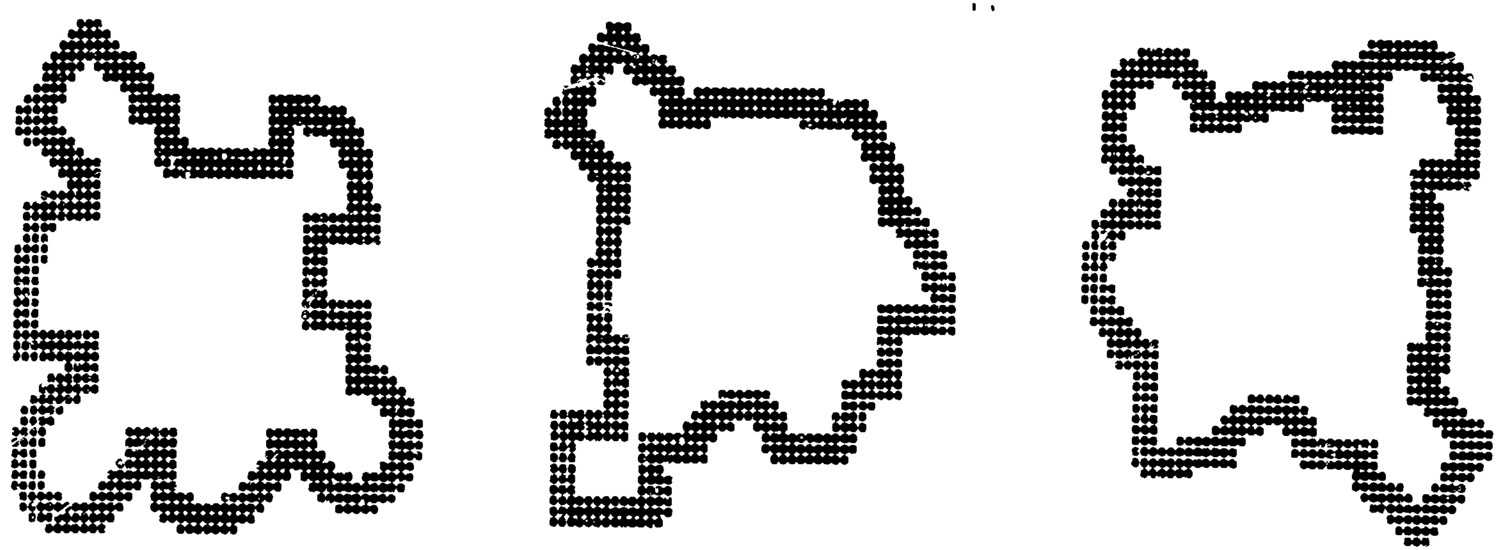

Fig. 3. Examples of patterns produced by the Vargus 10 system.

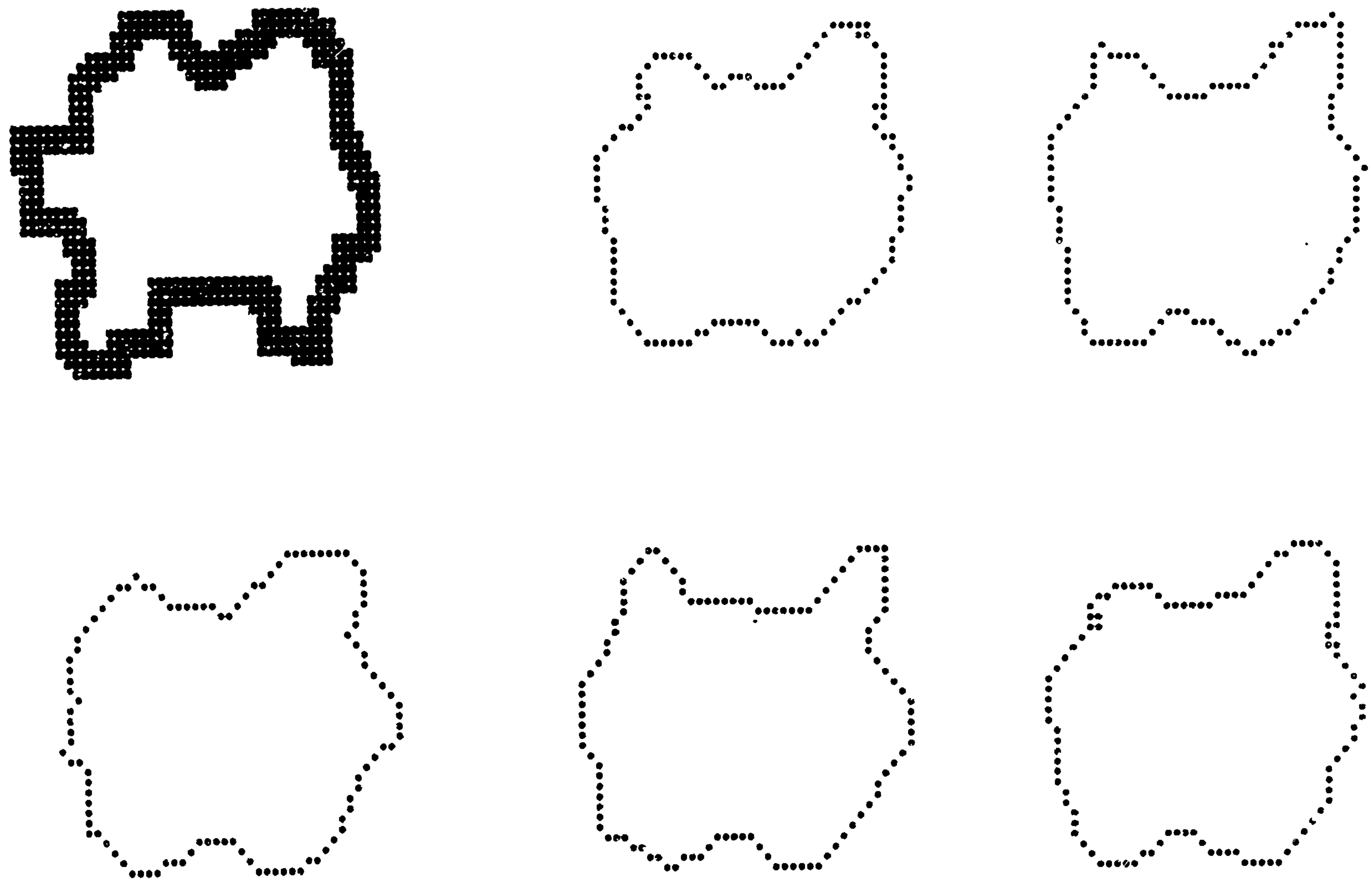

Fig. 4. Examples of variants produced by the Vargus 11 system from a prototype generated by the Vargus 10.

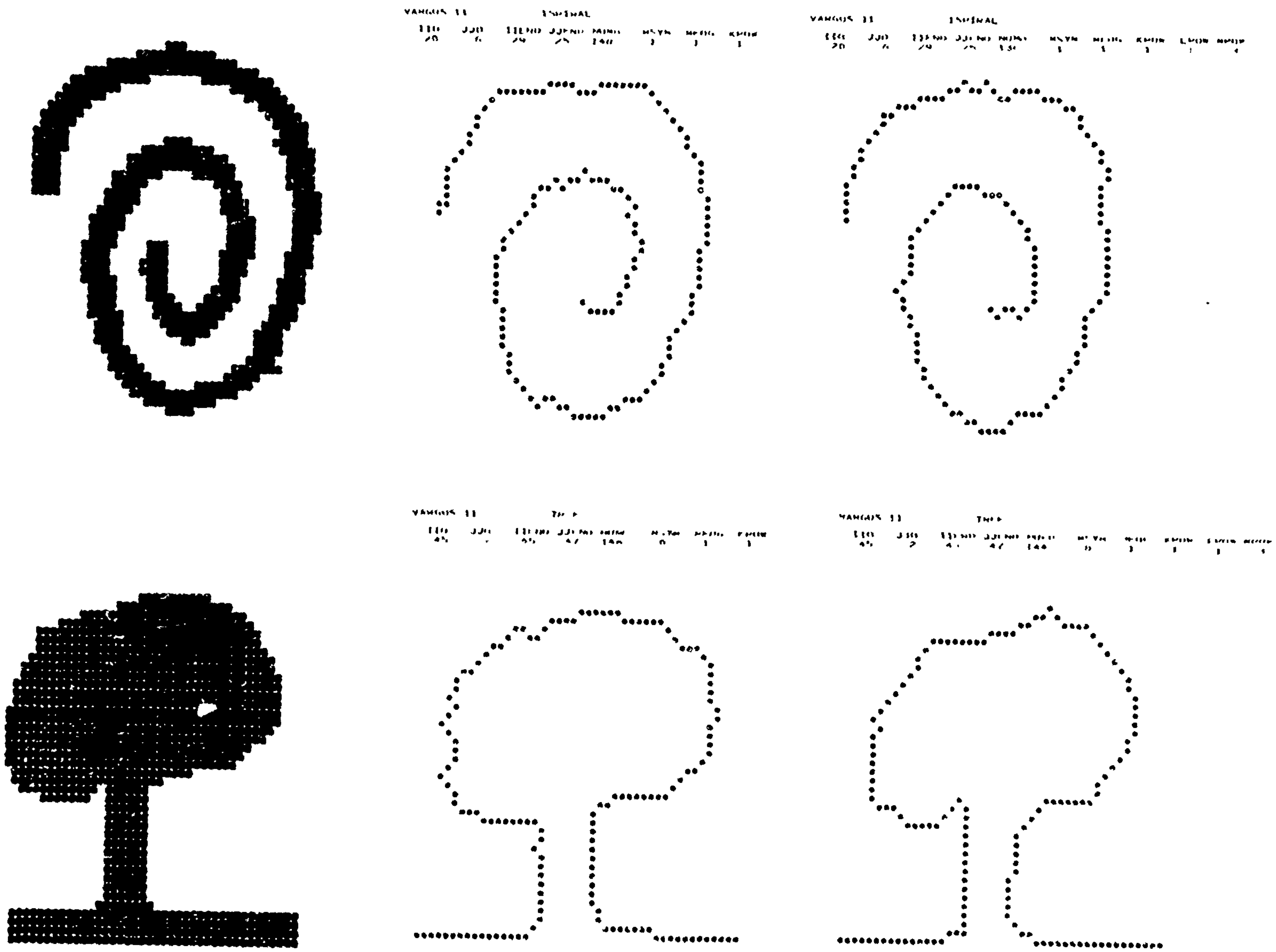

Fig. 5. Examples of Vargus 11 patterns produced from familiar prototypes (left).

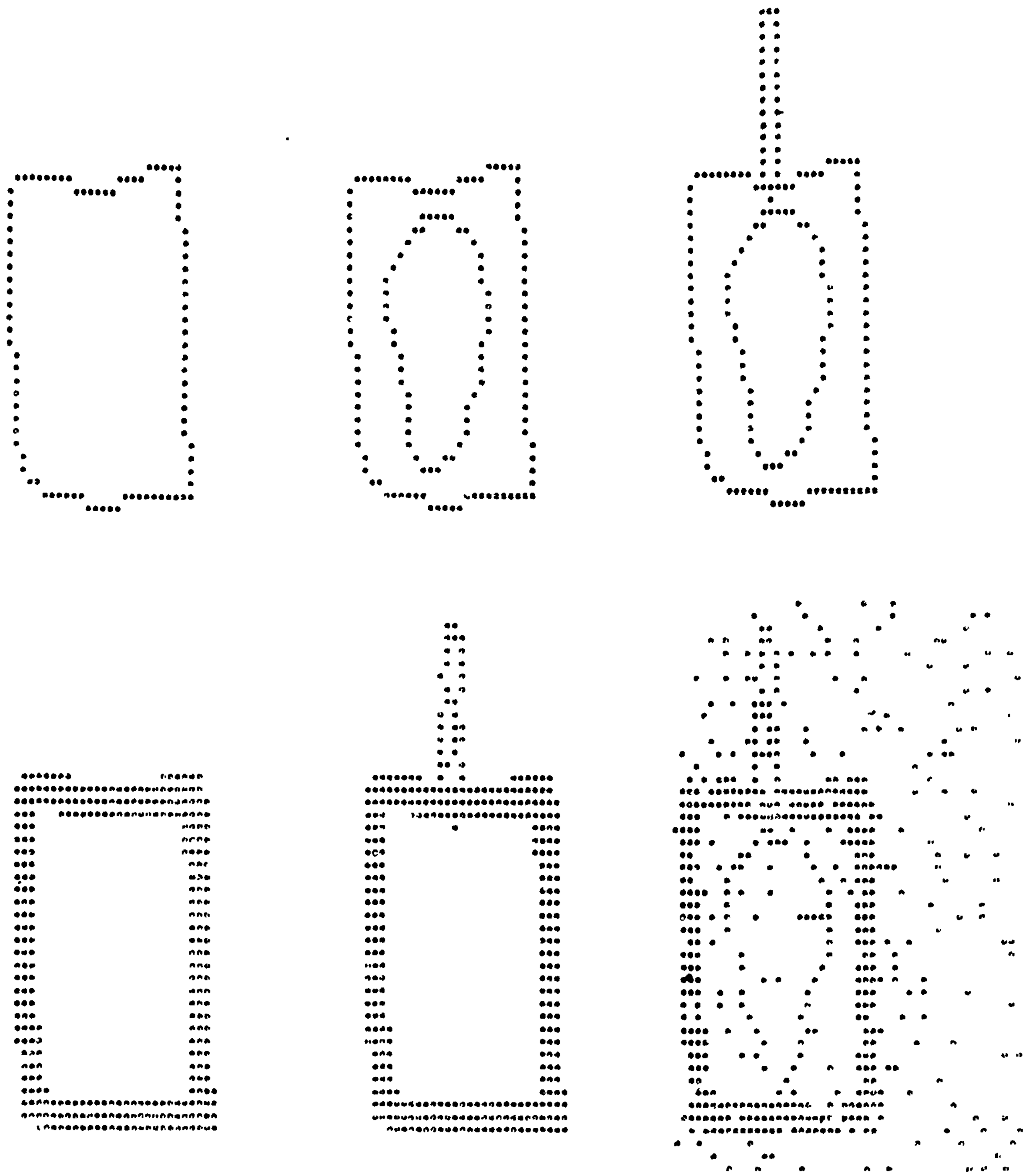

Fig. 6. Examples of Vargus 11 patterns used to construct a familiar object (a tank). The three parts of the tank (body, turret, gun) were sketched separately and then combined. In the lower example, the body outline was widened to make it more distinguishable and the final result was degraded by the introduction of a moderate amount of visual noise.

IMAGE INTERPRETATION RESEARCH

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INTRODUCTION

The scope of the U. S. Army Behavioral Science Research Laboratory's research program can be inferred from a brief look at the four research areas around which its current efforts are organized. BESRL is a Class II activity of the Army's Office of the Chief of Research and Development. The present program of research as approved by the Chief of Research and Development includes the following research areas;

1. Personnel Management Research--Selection: Predicting human performance effectiveness. Representative Tasks--Optimum Distribution of Individual Abilities for Unit Effectiveness; Development of Culture-Fair Tests for Selection and Classification in Selected Countries.

2. Personnel Management Research--Manpower Management: Evaluating and selecting personnel management policies through operations research modeling.

3. Human Performance Experimentation: Improving functional portions of performance (critical behavior in jobs). Representative Tasks--Dependable Performance in Monitor Jobs; Human Performance Experimentation in Night Operations.

4. Manned Systems Research: Improving total systems performance as relates to human performance (groups of jobs). Representative Tasks--The Determination of Interpreter Techniques in a Surveillance Facility; Influence of Displays on Image Interpreter Performance.

Under the four broad research areas above only a partial listing of the tasks being conducted has been presented. The content of the remaining portion of this paper will center on Manned Systems Research in general and the two tasks cited in particular. In these two tasks a number of experiments have been conducted to determine the relative importance of the techniques and displays used by the Army image interpreter in the process of extracting intelligence information from aerial reconnaissance imagery. All studies described are limited to the photographic sensor but our research program includes work with imagery from other sensors as well. While pattern perception research may involve any of the sensory modalities, the research studies reported in this paper are primarily concerned with visual stimuli.

A Partial Description of the Image Interpreter's Task

The image interpreter is the focal point in the generation of intelligence information from a reconnaissance mission. He is required to search the acquired imagery and detect and identify those objects specified on his list of required targets. He must do this rapidly, accurately, and completely. He has been trained in the skills of image interpretation and he is provided with tools and display devices that are judged to be adequate for the accomplishment of the job in a satisfactory manner. Even when we restrict our consideration of his task to the analysis of photographic imagery, the difficult nature of his job becomes obvious when we consider the variations that may occur from one situation to the next. For example, the photo scale may vary widely from very large scale to extremely small scale. The quality of the imagery may vary due to poor light conditions during acquisition, unstable conditions in the aerial platform due to rough air or other causes, processing errors, and so forth. The terrain and the type of objects for which he is required to search will cause the task to be variable. The patterns for which the interpreter is searching are constantly changing from one time to the next.

The interpreter has been trained in the recognition of the cues and signatures associated with specific types of tactical targets. These he may be able to recall without the use of reference aids or interpretation keys. For objects outside of his experience he refers to these key materials. These provide him with pictorial information which may include vertical, oblique, and side views as well as verbal description and actual physical dimensions. Just how well the average image interpreter is able to accomplish this pattern recognition task [illegible] been assessed empirically.

Completeness and Accuracy of Information Extraction

The motivation for instituting research on the human factors that are important to success in image interpretation came as the result of early exploratory studies of the accuracy and completeness of interpreter performance. Completeness and accuracy of interpretation are two measures that are frequently used to assess the excellence of interpreter skill. Completeness is defined as the ratio of the number of correct responses made by the interpreter to the total number of correct responses that were possible. Accuracy is the number of correct responses made by the interpreter expressed as a proportion of the total number of responses made by him--both correct and incorrect. In order to get a precise value for these two measures it is necessary that we know exactly what was present on the ground at the time the image was taken. Such information is called "ground truth" and quite obviously such truth is not usually available in operational imagery. Two studies were conducted quite early in the study of interpreter performance and those results are summarized in the following paragraphs.

Table 1 shows the mean completeness with which a group of interpreters extracted information from nine pieces of photographic imagery. In column two the ground truth for these images is given and in column three

the average number of targets found by these interpreters is given. The fourth column lists the average completeness for each of the nine images and gives the overall average completeness. On the average, less than four tenths of the information contained in the imagery was successfully extracted.

Table 2 contains data from another study on the accuracy of interpretation. Imagery acquired over nine different sites was the stimulus material. Number 1 was an image of the North American Aviation Plant in Columbus, Ohio and the other eight can be similarly described. The interpreters were experienced with from five to fifteen years of photo-interpretation experience. They were required to search for specified strategic targets in this imagery which varied in scale from 1:10,000 to 1:20,000. The accuracy of performance ranges from a low of 39 percent to a high of 61 percent with an overall average of 50 percent. This result can be stated as showing that these interpreters reported one false target for each real target reported. The user of such information has one chance in two that the specific target reported, upon which he might base a decision, is really there.

The foregoing results have been substantiated by many studies. While the numerical values for completeness and accuracy vary from one study to the next, the results reported here are typical. The amount of time allowed for interpretation is found to have an effect that is represented in Figure 1. Given sufficient time, the interpreter may finally achieve a relatively high level of completeness. However, he also finds more and more non-targets which he reports as targets and thus his accuracy of interpretation becomes extremely low. The identification of a non-target as a target is termed a "false alarm" or referred to as an "invention."

These sample studies indicate that there is a need for improving performance in extracting intelligence information from aerial photographic missions. Several research studies with such an objective are reported in the following sections of this paper. The studies chosen were selected because they parallel the potential coupling suggestions contained in one of the progress reports submitted by The Institute for Cognitive Research on their THEMIS supported work on Pattern Perception Research.

INTERPRETER SELECTION

The first thought that might occur to a mental-test oriented research psychologist would be that performance could be improved by selecting men for interpretation training who possess the requisite skills for doing that job. Such an approach was taken by Martinek, Sadacca, and Burke (1). Their investigation of the selection procedures used at the beginning of their study showed:

Officer Qualifications- Trainees must be regular army or reserve officers on active duty below the grade of Lieutenant Colonel. The Trainee's present or anticipated assignment must require the performance of or a familiarity with image interpreter duties.

Enlisted Trainee Qualifications- The enlisted trainee must have a General Technical Aptitude Area Score of 100 or above (GT Score = ½ of the Verbal Score plus the Arithmetic Reasoning Test Score; these part scores are portions of the Army Classification Battery). The trainee must have completed high school algebra or geometry courses or have achieved a standard score of 45 or higher on the equivalent high school level General Education Development Test. Each man chosen for training must have a minimum of 16 months of service remaining upon completion of the course.

General Qualifications- All trainees must have distance vision correctible to 20/20 and near vision correctible to 14/14 inches, normal stereoscopic acuity, and normal color perception.

In addition to the specific educational requirements, preference is to be given to men with formal training in geology, geography, and mathematics. The individual's expressed desire for such training is to be given consideration. However, no objective means of weighting these achievement and preference aspects is provided for the guidance of commanders responsible for filling quotas for the interpretation course.

Selecting Predictors of Interpretation Proficiency

Based upon previous research studies and upon educated guesses, a battery of potential predictor variables was assembled. Tests of spatial ability, perceptual speed, reasoning, memory, verbal skill, visual acuity, and general information were combined with several personal data records. Two criterion measures of success in image interpretation were established. The first was the final grade made in the image interpretation course while the second was the number of correct responses made in a practical exercise of interpretation performance constructed specifically for this purpose.

This battery of predictor variables was given to a total of 120 officers and 65 enlisted men prior to the start of a number of different classes in the image interpretation course. As each class completed the entire course, the class members were given the practical performance interpretation tasks. Each man's final course grade and his score on the practical test were recorded on the same score matrix that contained his record for the predictor variable battery. Correlations were computed between each predictor and the several criterion measures. The Wherry-Doolittle Method for selecting predictors was used to determine the set of predictor variables yielding the highest multiple correlation for each criterion.

Officer Prediction

A two-predictor test battery was found to be sufficient for predicting the criterion measures. The Image Orientation Test and the Image Interpreter Information Test yielded a multiple correlation of .63 with Course Grade and .62 with the Tactical Rights Score. This two-test battery requires about one hour for administration. This predictor battery was cross validated on another sample of 83 officer trainees and the multiple correlations

obtained were .66 for Final Course Grade and .52 for the Tactical Rights Score.

Enlisted Interpreter Selection

The same general approach was taken for the enlisted sample. One additional measure was used as a potential predictor, the General Technical Aptitude Area Score from the Army Classification Battery. The simple correlation between the GT Score and Final Course Grade was .76 and with the Tactical Rights Score the correlation was .60. The Wherry-Doolittle Method indicated that the addition of other predictor variables did not result in a significant improvement in prediction. The authors recommended that selection of enlisted trainees be based upon GT Score and that, if at some future date, it became necessary to lower the GT Score level in order to fill quotas, the selection study be repeated at that time. During the time that the selection study was being repeated, the selection battery found useful for officer selection could be used to select enlisted trainees.

Conclusions

The number of trainees who successfully complete the Image Interpretation Course can be increased by means of additional selection. The same selection measures correlate well with the number of Tactical Rights made in a practical test of image interpretation. The number of Tactical Wrong Responses were not predictable. Apparently, erroneous responses are idiosyncratic and vary in a random manner.

Of what use are these results? Suppose that at the present time, 70 percent of those starting the course complete it satisfactorily. Assume that applicants are selected by the screening methods in force at the start of this selection study and that these applicants are then given the recommended predictor battery which for simplicity we will assume has a multiple correlation of .65 with final course grade. If all applicants are admitted to the course we should expect that about 70 percent of them would complete the course in a satisfactory manner. However, if only half of the group of applicants is admitted--the 50 percent with the highest scores on the selection battery--then we would expect almost 90 percent of them to complete the course satisfactorily. The determining factor in the implementation of such a selection procedure is that there must be an adequate applicant group available.

While the results of this study are encouraging, it is apparent that there is a considerable amount of variance in the criterion measures set for this study that is still unexplained. The multiple correlations obtained between predictors and the criterion measures ranged from .50 to about .75. On the average, less than half of the criterion variance has been explained or accounted for. There is still much room for improvement.

ERROR KEY STUDY

The predictor variables used in the selection study were found to be of little use for selecting men who made few errors in tactical image interpretation. Therefore, Martinek and Sadacca (2) conceived of another approach to the problem of reducing the number of errors made by interpreters.

Sixty interpreters were given the assignment of searching for specific tactical targets in 90 photographic prints. Their responses were scored and the location of their erroneous responses plotted on the actual photographic prints. An expert interpreter viewed the image location of each error and made a subjective appraisal concerning the likely cause. It was found that 80 percent of all erroneous responses were attributed to six general causes by this expert. A description of two of the causes will suffice to describe the nature of these cause categories. The Tree Shadow Error Cause was very common. Here the shadow of a tree falling on a road was frequently misidentified as a vehicle. A second type of error was called the Tracks Error Cause. Tracks across an open piece of terrain and then into a wooded area where complete concealment was possible were often associated with a vehicle response even though the vehicle was not there. With this list of error causes, Martinek and Sadacca conducted an experiment directed toward reducing interpretation errors by giving prior instruction concerning the judged causes of errors.

Development of the Experimental Reference Materials

The Error Key materials were developed by selecting photographic examples demonstrating the six error causes. These images were annotated and instructional material written for presenting these keys to the interpreters. The reference materials were taken from the same photographic mission that was used for the source of the experimental test imagery. In this way, the key material was of similar scale and terrain composition but, of course, did not include precisely the same pieces of imagery.

The Rights Key was the term given to the more conventional type of interpretation key. Here the required targets as they actually appeared in the mission imagery was used for the reference key. This key varied from the normal key in that it was specifically tailored to the imagery for which it was to be used.

Conduct of the Experiment

Fifty-one officers and enlisted men who were completing the Image Interpretation Course were used as the interpreters. Three equated groups of seventeen men each were established on the basis of their performance on three standard measures of interpretation performance. Group A was given no reference material and served as the experimental control group. Group B was given instruction in the use of the Rights Key and permitted to use the key during the experimental task. Group C was given prior instruction in the use of the Error Key and had this key available to them

during the experiment.

All three groups of subjects searched for and identified objects on a common target list. Each man viewed 40 prints from one mission with a two-hour time limit and 25 pieces of imagery from a second mission with a one-hour time limit. Each man's responses were scored to determine the number of correct and incorrect responses.

Results

Table 3 gives the mean performance of the three experimental groups. The use of reference materials had no significant effect on the number of correct identifications. It had been anticipated that Group B using the Rights Key would have performed better than the other two groups. This was not supported by the experiment. For the number of erroneous responses, Group C using the Error Key made significantly fewer errors. Since the accuracy index depends upon the number of erroneous responses, the finding that Group C was more accurate is not surprising. These results are of interest but there is a need for a more detailed study of error causes.

SUMMATION

The photographic sensor was the only one considered in this paper. The two studies cited indicate that interpreter performance can be enhanced through selection of personnel and by instructing him as to the common causes of interpretation errors.

For interpretation of imagery from other sensors there will be unique aspects associated with these sensor images that will require the consideration of other variables. In radar imagery, for example, the target return may show no recognizable form in the conventional sense so that quite different cues and signatures will be needed if identification is to be made. Definition of the target signatures for both conventional and non-conventional imagery is needed.

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Table 1

COMPLETENESS OF INFORMATION EXTRACTION

Image Number	Ground Truth	Average Correct	Percent Completeness
1	18	6	34
2	48	26	54
3	16	5	34
4	17	6	36
5	13	6	43
6	27	8	28
7	31	14	44
8	28	11	39
9	7	3	39
Average	23	9	39

Table 2

ACCURACY OF INFORMATION EXTRACTION

Target Site	Percent Accuracy
1. North American	45
2. Norfolk	5[illegible]
3. New London	56
4. Letterkenny	39
5. Fort Monmouth	54
6. Wright Patterson	49
7. Dow	61
8. Little Creek	46
9. Loring	41
Average	50

Table 3

MEAN RIGHT, WRONG, AND ACCURACY SCORE FOR THREE EXPERIMENTAL GROUPS ON T[illegible] PERFORMANCE MEASURES

Experimental Group	Right Score	Wrong Score	Accuracy Score
Control (A)	13.5	19.0	.46
Rights Key (B)	14.4	19.6	.47
Error Key (C)	12.9	12.8 [a]	.58 [b]

[a] A + B - 2C comparison significant at .05 level.

[b] B - C comparison significant at .05 level.

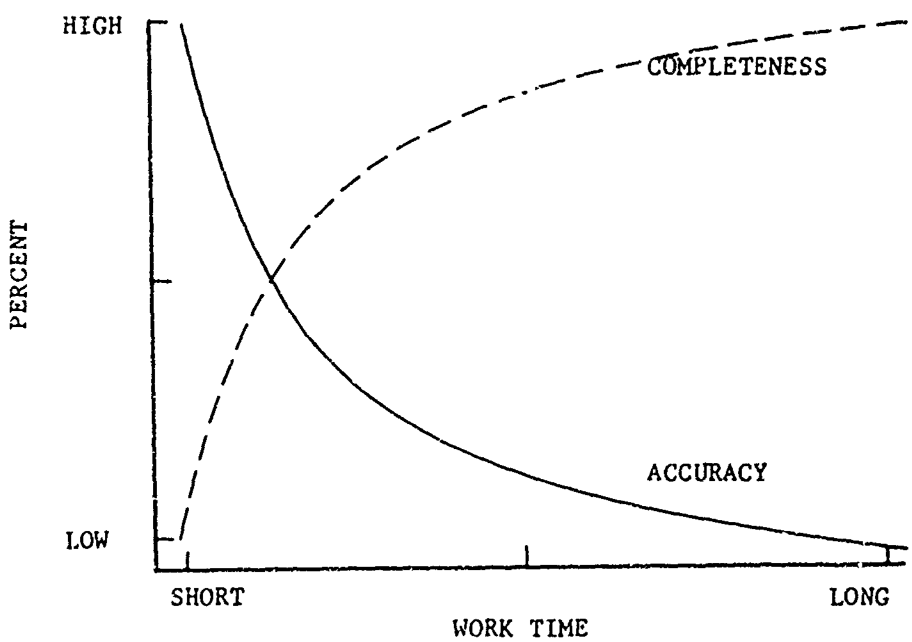

Figure 1. ACCURACY AND COMPLETENESS RELATED TO TIME

PATTERN RECOGNITION STUDIES AT THE BALLISTIC RESEARCH LABORATORIES

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INTRODUCTION

Tactical targets of concern to the Army are often difficult to acquire and destroy because they are usually small, frequently mobile and subjected to camouflage. Moreover, ground and near ground observations of vehicles, emplacements, and other artifacts as well as personnel are complicated by the environment in which they occur. Targets are easily concealed by merging them with background of high clutter. For example, techniques are employed to modify thermal emissions of targets and to control the reflection of radar signals from targets in such a manner that the target blends with the surrounding area.

Targets and backgrounds must be remotely sensed under a wide range of environmental conditions. Their characteristics are measured in terms of radiation and therefore depend upon properties such as thermal conductivity, thermal capacity, convection and surface condition. The measurements also depend upon the propagation of the radiation in the near earth atmosphere. Some of the propagation effects are the absorption and scattering of electromagnetic radiation by both natural and artificial constituents. In addition the remote measurements are also affected by geomorphic, floral and cultural environments and by meteorological conditions.

Because of the many variables associated with the problem, the detailed descriptions of targets and backgrounds, including tactical targets of opportunity, have been generally neglected. However, the need exists for real time information about targets especially in regard to their presence, location, type, quantity and state of readiness.

At present the Ballistic Research Laboratories have in-house studies on target acquisition and missile guidance. One team is investigating the pattern detection capabilities and limitations of sensors operating in the millimeter wave and visible regions of the spectrum. In another area of target detection, the Ballistic Research Laboratories is supporting an Illinois Institute of Technology Research Institute contract on detection of human effluents. Another group is examining the potential of image correlation techniques for missile guidance. In addition, another group is engaged in mathematical studies relating to pattern recognition. Details of some of these studies will be described.

TARGET ACQUISITION

The purpose of the work is to develop methods of target acquisition by theoretical and experimental analyses of target and background signatures. Millimeter wave and photographic signatures have been selected as reasonable sources of input data for initial investigations.

Millimeter Wave Research

Metal targets appear as low temperature sources to a millimeter wave radiometer since they reflect the relatively cool sky. Foliage and terrain have low reflectivity and high emissivity properties and therefore appear to the radiometer to be at the ambient temperature. The contrast presented by metal targets and background offers the possibility of passive acquisition. Millimeter wave studies are underway to determine basic propagation parameters from which predictions of pointing error, range, and meteorological limitations can be inferred. Measurements of reflection coefficient, attenuation, and precipitation effects are being made. A problem dealing with the radiometric detection of a metal target obscured by foliage has been modeled. Statistical techniques were used to construct decision functions based on probability distributions inferred from radiometric measurements of target and non-target scenes. In addition to this mathematical approach, foliage models have been fabricated and data taken using a 35 GHz radiometer. Foliage obscuration models for radiometric systems composed of microwave absorbers perforated by holes of various size and shape are used in sequence in order that the dependence of the amount of obscuration on size and shape parameters can be determined. The amount of obscuration was found to vary directly with the perimeter to area ratio, that is for example, a rectangular cover causes more radiometric obscuration than a circular cover of the same area. The correction factor between radiometric obscuration and visual obscuration appears to have a wavelength dependence and more data are being acquired to determine the relationship.

Texture Measurements on Photographs of Tanks

A study is being conducted of the applicability of local texture measurements for detecting tank images in digitized photographs. Each photograph portrays a medium tank situated in a typical environment which includes a dense tree background and an open, grassy foreground. Gray scale, gradient, and Laplacian transformations were obtained from target and background signatures. From these transformations a wide variety of texture measurements were made including two kinds of pattern detail, horizonal line content and various geometrical moments.

Some conclusions and inferences drawn from this investigation are as follows:

1. Laplacian and gradient preprocessing serve to enhance the separability between target scenes and background scenes.

2. Several of the moment features appear to offer the greatest potential for discrimination between the selected classes.

3. A normalized count of horizontal edges provides good separability between classes for the samples considered.

Detection and Identification of Chemical Signatures

For the last three years Dr. A. Dravniek's of Illinois Institute of Technology Research Institute has been working on the detection of human effluents. During this time he has designed and built an apparatus which enables him to collect effluents from humans in a specially designed trap. He has also devised methods of collecting air samples from various environments and of analyzing them by means of gas chromatography. The chromatograms obtained contain about 50 peaks. Many of these are poorly resolved and overlap each other. Also, few of the peaks have been identified. Despite these reservations, an analysis of 65 human and 10 non-human chromatograms, while inconclusive, reveals a glimmer of promise for using the chromatograph as a detector. We hope to continue supporting some research in this area. The immediate aims will be to

1. achieve better peak resolution

2. use mass spectrometry to identify the peaks

3. establish error figures associated with repeatability of results from both chromatograms and mass spectra.

MISSILE GUIDANCE

Image Correlation

The aim of this phase of research is to determine by theoretical and experimental studies the technical feasibility of image correlation methods in missiles homing on tactical targets. The ultimate goal is to generate steering signals by correlating the outputs of remote missile-borne sensors under various environmental conditions representing tactical situations. Early studies were made to determine which characteristics of the correlation function were useful in the tactical assault missile application. Specifically, the correlation functions for typical target signatures were studied to examine the effects of environmental parameters upon the shape of the correlation function. These parameters include the size and shape of the aperture determining the field of view, perspective changes and scaling factors associated

with range closure and various distributions of information in the target signatures. These studies indicated the need for limiting the size of the field of view to the target itself in order to exclude extraneous background detail which tends to degrade correlation rapidly with range closure and for moving targets. The basic correlation function has been demonstrated to have characteristically a local peak indicating the spatial registration of target signatures. This peak does not, in general, exhibit sufficient symmetry to make this property a useful key to match peak discrimination. Also, the sharpness of the match peak in the correlation function is found to be unreliable for discriminating this peak. The amplitude characteristics of the correlation function provide the greatest promise for use in the guidance application.

To make use of the amplitude characteristics, it was found that some form of normalization is required to reduce the effects of using finite apertures. Three normalization methods, one using signature pattern norms and two using pattern means, have been studied. The effectiveness of these methods for normalizing correlation functions generated with a representative sample of signatures obtained by remote sensing of targets and backgrounds has been demonstrated.

The effects of range closure on the correlation process were considered in relation to the use of limited fields of view containing information from typical target signatures. The inherent scale changes accompanying range closure degrade the correlation function and have been shown to be responsible for systematic aiming errors for typical situations. The causes for this degradation have been investigated.

An investigation of the effects of target aspect changes upon image correlation functions has been conducted. Correlation function profiles have been examined by using a set of photographic transparencies which simulate acquired signatures having various amount of controlled aspect change. Quantitative measurements of the degradation produced in typical correlation functions by aspect changes have been obtained.

RELATED MATHEMATICAL STUDIES

Mixture Problems

An analysis has been completed on a class of "mixture" problems that arise in pattern classification studies. The mixture problems arise when one wishes to detect an event of interest by scanning a photograph or natural scene with a sensor. Each measurement obtained from the sensor may represent background only, signal only, or a combination of signal and background. The problem is to decide, from

a measurement or sequence of measurements, which case prevails. Required inputs for this decision problem are probability distribution functions associated with measurements obtained from each of the possible sources. For a broad class of sensors it was possible to **compute** the probability distribution function for the class of observations representing a mixture of signal and background from the distribution functions for the signal class and the background class. The mixture distributions, H(u), is of the form

$$H(u) = \int_W L(u|w)dK(w)$$

where L = distribution function depending on a parameter w

$K(w)$ = distribution function associated with w.

An inverse problem to that of finding H(u) is also being studied. This problem arises in several contexts in pattern analyses. The problem reads as follows: Let $\Omega = \{K(w)\}$ be a class of distributions defined on the real line. For each value of w, let $L(u|w)$ be a distribution function. Let $H(u) = \int_W L(u|w)dK(w)$ be a mixture distribution. Let $u_1, u_2, \ldots$ be a sequence of independent observations selected according to a mixture H(u). From these observations one wishes to determine an estimate of K(w).

APPLIED PERCEPTUAL PROBLEMS IN AIRCRAFT RECOGNITION AND SITUATION RECOGNITION

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HumRRO's prime mission is to provide training research for the Army. While the majority of our research is involved in training methodology, an increasing amount of research is concerned with problems of visual recognition and classification. At Division No. 5, a large portion of our research is devoted to developing efficient procedures for training these perceptual skills. While we have considerable experience in training perceptual skills, we have not yet developed an adequate taxonomy of perceptual learning. Nor have we experienced a great deal of success by applying traditional learning theory to these tasks. This state of affairs indicates that we have not yet found an adequate theoretical conceptualization for our research efforts.

Pattern recognition models are of prime interest to those of us concerned with the training of perceptual skills. The pattern recognition models give us an indication of the manner in which man may process visual information. This, in turn, gives us a conceptual base for determining what perceptual skills are relevant and the order in which they may be most efficiently trained.

I would like to spend some time discussing two research tasks at Division No. 5. The first task is called MANICON, which is an acronym for <u>man in control</u>. The research effort is currently in the planning state. The MANICON research is concerned with man's capability in the manual command and control of highly automated air defense weapon systems, such as the SENTINAL and NIKE X anti-ballistic missile system.

The Army agency sponsoring the study, in conjunction with HumRRO research, has designed a large-scale command and control simulation facility. HumRRO will participate in the use of this facility. One of the problems which we will consider concerns man's ability to perform the complex decision functions involved in the tactical engagement situation.

While I cannot go into detail concerning the information inputs, it is apparent that each command decision involves a large number of contingencies. The overall strategy of the defense depends upon the particular threat configuration

presented as well as certain intelligence and environmental information. In a sense, the intelligence and environmental information establish some limits on likely threat configurations. One of man's roles would be to recognize an existing attack configuration as belonging to a subset of possible attack configurations. If the threat is appropriately classified, the system may employ an optimal or near optimal defense.

While it may not be apparent, this task may be considered as a problem in pattern recognition. In effect, the pattern elements are presented sequentially, step-by-step, and the observer must decide, either at each step or as soon as possible, which pattern is being presented. This approach assumes that the *a priori* intelligence information forms the initial elements of a pattern. The play-by-play unfolding of the attack forms the latter part of the pattern. Based on the information available to the viewer, he must determine the most likely attack configuration being thrust at him. This approach also assumes that a reasonably small number of prototype attack configurations exist and that all possible attack configurations are variations of these prototype patterns. The training problem now becomes one of teaching a limited number of prototype attack configurations and the variability that exists within the prototype patterns.

When considered in this context, the task is very similar to the research using VARGUS-7 (Evans, 1967) stimuli. More important, the theoretical conceptualization concerning performance on VARGUS-7 stimuli may be brought to bear on the decision task.

While this is an obvious oversimplification of the existant problem, the point is rather clear. The availability of a theoretical model of the task in conjunction with the comprehensive system's simulator will allow us to make a systematic approach to a very complex training problem. As I mentioned, the research is presently in the planning stages and we have no experimental data to offer. We are, however, optimistic in that much of the schematic concept formation research and conceptualization has a rather direct parallel in this type of situation recognition task.

A more classic example of human pattern recognition research is being conducted at Division No. 5 under Work Unit STAR. The mission of Work Unit STAR is to develop concepts of aircraft recognition training applicable to forward area air defense. The British developed a training methodology which relied heavily on image analysis. The

observers were taught a nomenclature system which distinguished characteristics of the wing, engine, fuselage, and tail structures. Early American attempts at aircraft recognition combined the British system with slide training. Subsequently, this combination was heavily influenced by Samuel Renshaw's gestalt orientation. Very short exposure times were employed and the observers were discouraged from attempting any image analysis.

Recent military training has combined these two systems by teaching distinguishing characteristics and providing tachistoscopic training images.

Several problems were apparent in the current training program. Research by Gibson during World War II, and more recent work by Gavurin have indicated that short exposure times produce lower proficiency test scores and more errors in training than do longer training exposure times. It was also apparent that the stimulus material needed revising since trainees were able to recognize an aircraft by the background characteristics rather than the aircraft characteristics. The first order of business was to construct a set of stimulus slides which presented a homogeneous background.

The first research study investigated a simple paired-associate approach to the training problem. The paired-associate approach was most discouraging and more recent studies indicate that average achievement levels of 50% to 60% are about the best that can be obtained with this approach and any reasonable set of aircraft.

A training package was then constructed which follows the British system of training aircraft recognition in that verbal descriptors of discriminating features of the aircraft were taught to trainees. These verbal descriptors were presented in simple English rather than aeronautical engineering terminology. The training method consisted of presenting slides of two different aircraft. The trainees were asked to describe differences between the aircraft. The instructor discouraged the description of similarities or detailed feature differences. The trainees continued the program until they could correctly identify 95% of the aircraft. The research indicated that an average of 50 minutes was required to learn each aircraft in the program.

This basic technique has been used in a number of studies with similar results. The most recent version of this training involves the learning of cues which differentiate specific aircraft within a subset of aircraft. The training program

is specific to a preselected set of aircraft and is useable with at least 16 aircraft. A printed version of the training procedure is now being constructed for individual self-paced use.

One of our current interests is in determining the minimum number of training views of an aircraft that will produce uniform performance across all possible views. One of the institute's graduate students, Bill Rankin, conducted some of the early studies in this area. One of the interesting findings of this research is that generalization is far from uniform across the views. It appears that generalization from the near head-on views is quite restricted. This research has resulted in selecting 9 training views which appear to provide a relatively flat generalization gradient across all possible views.

We are also investigating aircraft recognition from a somewhat simpler point of view. It has often been noted that a soldier only needs to categorize an aircraft as friendly or hostile. This approach has several deficiencies as a training approach yet it may provide considerable information concerning the stimulus characteristics utilized by the subject in his classification. We have constructed a computer program which generates airplane patterns from a prototype pattern. The airplane patterns vary in wing length, horizontal stabilizer length, vertical stabilizer length, wing location, and horizontal stabilizer location. These patterns were constructed by mapping a VARGUS-9 (Evans and Mueller, 1967) mathematical pattern into the airplane configuration. The VARGUS-9 methodology and pattern descriptors are therefore applicable. A pilot study has been conducted to determine the appropriate range of stimulus difficulty. We are currently collecting data to determine if performance will differ on histoform and airplane versions of the same mathematical pattern. We also hope to construct computer simulation programs which will simulate human performance with these patterns.

As with the MANICON research, the machine pattern recognition literature has parallels in the problem of training aircraft recognition. As I mentioned before, the machine pattern recognition models provide a conceptualization for the training of human pattern recognition skills. I expect that those of us involved in the training of perceptual skills will draw more heavily on this literature in the future.

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PATTERN RECOGNITION RESEARCH AT AFCRL

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INTRODUCTION

The following few pages are an attempt to summarize work in visual pattern recognition currently in progress within the Data Sciences Laboratory at Air Force Cambridge Research Laboratories. The Data Sciences Laboratory has the assignment of conducting research in the computer and communications areas and does so on a broad range of topics. Four projects, at least, among those currently under way are concerned with some aspect of pattern recognition.

1. Herbert Glucksman has been developing techniques for recognition of machine-printed characters. The emphasis in this work is on techniques which can be implemented in fast special-purpose hardware and are effective over a range of type fonts. This work is closely connected with other work in the laboratory on large-scale logic arrays, in that the choice of the properties computed on the character to be classified was influenced by the possibility of implementation by such hardware. The scheme works something like this: the character is superimposed on a matrix of cells, so that each cell is either "on" (i.e. covered by part of the character) or

"off" (i.e., not covered). Then various operations propagating the on-or-off values from cell to adjacent cell are carried out. As suggested above, these operations are well suited to cellular array logic and can be carried out very rapidly. The results (30 in number in the present system) of these various types of propagation are then passed on to a relatively conventional decision-tree classification scheme. The recognition rates obtained in large-scale simulation on a digital computer are very good, and the speeds that should be obtainable from full hardware implementation are quite impressive.

2. Charlton Walter is concerned with problems requiring analysis of large amounts of sensor data (to, for example, detect signals in noise). The methodology he has been exploring for some time involves permitting the user to interact with a computer through a display in exploring and manipulating such data. For example, he may try various transformations of the N-space in which his sample points are plotted and observe how these operations affect the separation of different classes of data points. In particular, this interactive system has been used to compare various of the techniques of multivariate statistics used in pattern recognition with respect to their effectiveness in treating data possessing various special properties.

3. A branch of the laboratory under the direction

of J. Mott-Smith has been working in the area of image processing and pattern recognition. Much of the work of this group has been in smoothing, edging, etc. of photographs and thus is relevant to a preprocessing phase of visual pattern recognition. In addition, considerable work has been done on pattern classification or analysis <u>per se</u>. This work, principally by Otis Philbrick and Capt. Glen Wilson, is based to a considerable extent on the use of the so-called medial axis transformation, studied extensively over a period of years at AFCRL by Harry Blum. This transformation (of a closed contour, say) consists in propagating "waves" normal to the contour at uniform velocity, and noting the points where the wave fronts meet. The collection of such points, together with a "time of arrival" associated with each point, constitutes the transformed representation of the contour. This approach is frequently called a "stick-figure" one, since the result of the transformation frequently looks like a stylized "stick-figure" version of the object bounded by the original contour. The medial-axis transform has been applied by Wilson to extraction of aircraft silhouettes from noisy backgrounds in reconaissance photographs. Philbrick is using it as a component in a recognition program which works with hierarchical descriptions of objects based on the connectivity of the "stick-figure" representation, viewed as a graph.

4. The author's own research in pattern recognition concerns formalisms for describing structure in complex patterns and, in particular, what might be called "pattern grammars", that is, sets of rules describing pattern structure (for example, how a given object may be built up out of specified subobjects related in specified ways). A quite general formalism of this nature has been developed and corresponding analysis programs, capable of analyzing a (suitably preprocessed) pattern according to such a grammar, have been written and tested. Current work involves improving the existing formalism and analysis programs, interfacing them with preprocessing routines already existing elsewhere, and studying problems of "learning" or "inductive inference", using the existing formalism (that is, considering the problems associated with automatically generating--using a given stock of primitive object types and relationships--a "[illegible]" grammar describing a set of sample patterns).

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PSYCHOPHYSICAL MODELS FOR PATTERN PERCEPTION

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The conceptual origins of the psychophysical approach to pattern perception lie in the theoretical writings of J. J. Gibson (1950, 1959), who took the rather extreme position that every perceptual response could be shown to have an invariant relation to physically measurable properties of the stimulus. This point of view was completely at variance with the then dominant Gestalt position that form and pattern are properties which transcend physical measurement of the stimulus, since the primary determinants of the response were assumed to be the organization properties of the central nervous system. It was Gibson's contention that the lack of correspondence between the perceptual response and the physical stimulus was more apparent than real. He attributed it to a lack of sophistication in measuring stimulus properties. Essentially, he argued that perception was responsive to relations among, and combinations of, simple physical properties such as length, intensity, and duration. Proper identification of "higher-order" physical variables would permit the development of a multidimensional psychophysics of form and pattern perception.

At the same time that Gibson was challenging the Gestalt view of the unanalyzability of forms and patterns, psychologists were attempting to come to grips with another aspect of the same problem. Because there was no satisfactory system for describing and classifying forms and patterns, the particular stimuli used in a given experiment were selected rather haphazardly. Usually they consisted of geometric forms, of selected "real" objects, or of so-called nonsense figures drawn unsystematically by the experimenter. Consequently, the results of any given experiment in form perception could not be generalized to other situations unless exactly the same stimuli were involved. The task of developing a psychophysics of pattern perception, then, was twofold: (1) To produce form and pattern stimuli such that the results of a given experiment could be generalized beyond the particular stimuli used in that experiment; and (2) to identify "higher-order" physical measures capable of predicting perceptual responses to these stimuli.

The Problem of Stimulus Sampling

A number of solutions to the problem of generalizing

results across stimulus samples were proposed independently by different psychologists at about the same time (Fitts, et al., 1954; Attneave and Arnoult, 1956). All the proposed methods had in common the idea of randomly-determined differences between stimuli belonging to a single population. Each stimulus is constructed according to a set of rules, some of which are fixed and some of which require appeal to chance (e.g., a table of random numbers) at certain decision points. The set of rules taken as a whole implicitly specifies the population of all stimuli which could be constructed by those rules. Any particular set of stimuli constructed by those rules constitute a random sample from the population, since the differences between individual stimuli derive only from appeals to chance. It follows, therefore, that the results obtained with one stimulus sample should be replicable, within the limits imposed by sampling theory, with a new set of stimuli drawn from the same population.

Although these techniques for stimulus sampling represented a methodological advance of considerable value, they had two limitations: (1) They did not permit generalization across stimulus populations, and (2) they did not provide guides for generating samples represen- tive of specific stimulus problems of interest, e.g., aircraft, radar or sonar signals, etc. This latter problem, of course, is the one called <u>ecological validity</u> by Brunswik (1952) and is of particular concern in connection with fidelity of stimulation. Both limitations,however, can be overcome only by determining physical stimulus measures which are perceptually relevant.

The Problem of Physical Measurement

Physical measures of forms and patterns fall into two classes. One kind consists of analytical measures which constitute, essentially, the coding of the information needed to reproduce the stimulus. The other kind, which is of more interest here, attempts to get at exactly those Gestalt properties of form which were considered to be unanalyzable. Typically, these are "higher-order" measures in that they are combinations of simple measures or they are parameters of distributions of simple measures.

The first empirical attempt to account for the perception of forms in terms of higher-order physical measures was Attneave's (1957) investigation of complexity. He found that about 90% of the variance in judgments of figural complexity could be accounted for by a combination of measures involving such things as number of sides,

P^2/A, Angular Variability, Symmetry, and Curvature. Subsequent investigations of complexity showed that these same variables could account for comparable amounts of variance despite changes in the subject population, the kind of judgmental task used and, within-limits, the characteristics of the stimulus population (Elliott, 1958). Other studies applied the same approach to other kinds of judgments, such as size, familiarity, meaningfulness, and esthetic value, with varying degrees of success (Arnoult, 1960a, 1960b).

In order to generalize results across stimulus domains, however, it is necessary that one be able to estimate the parameters of the populations concerned. Vanderplas (1965), for example, examined interrelationships among a large number of physical measures obtained on 11 different samples of 100 stimuli each. A number of investigators (Vanderplas, 1965; Zusne, 1965; Brown and Owen, 1967) have developed and evaluated new physical measures, such as the moments of the distributions of angles and side lengths. Still other developments have involved hierarchical classification systems for physical measures (Michels and Zusne, 1965).

Currently the most extensive and sophisticated development of the psychophysical approach to form and pattern perception is represented in the work of Don Brown at Purdue. Brown and his associates have published a substantial number of methodological and empirical studies designed to investigate the effectiveness of the psychophysical approach. In a major methodological paper Brown and Owen (1967) performed a factor analysis of 80 physical measures applied to samples of 200 nonsense forms at each of five levels of complexity (number of sides). A subsequent experiment (Brown, 1968) investigated the utility of these factor scores in accounting for performance on a similarity rating task and a matching task. The detailed findings of these two papers are much too complicated to be summarized here, but Brown concluded that the general utility of this psychometric approach had been demonstrated.

Perhaps the most significant aspect of the psychophysical approach to form and pattern perception is the extent to which its development is tied to empirical procedures. The general objective is to find a psychological space and a physical space which can be mapped onto one another with a maximum amount of congruence. The psychological space is derived from performance measures obtained in perceptual tasks and so is sensitive to changes in the nature of the task and the kinds of measures obtained. There is no way in which the experimenter can know the minimum number of different psychological spaces required to account for all

kinds of perception. Ideally, of course, a single model of psychological space would prove adequate for all kinds of tasks, but there is no way to know in advance what that model might be.

A similar set of problems faces the theorist attempting to generate a physical space appropriate to form and pattern stimuli. As a number of writers have emphasized (Attneave, 1959; Brown and Owen, 1967), such stimuli vary both in "logon" content (the kinds of attributes or dimensions of variation) and in "metron" content (units of measurement along each attribute or dimension). Unsatisfactory matching of the psychological and physical spaces can be attributed to one or more causes: (1) The "higher-order" variables chosen for measurement define a physical space inappropriate to the psychological space; (2) the physical space is appropriate but not enough higher-order variables have been studied; (3) the psychological space is inadequately defined because of unreliability of the performance measures chosen. Under these conditions the experimenter is forced to rely to a considerable extent upon "cut-and-try" procedures. It is even difficult to know when a particular model, or even a particular measure, should be abandoned as unproductive. Improvements can generally be achieved by elaborating or complicating the model, but frequently the improvement in prediction of performance on a particular task is achieved at the cost of reducing the generality of the model or at the cost of increasing the complexity of the model to an extent that is out of proportion to the amount of improvement.

What is the current status of the psychophysical approach to form and pattern perception? If it has accomplished nothing else, it has succeeded in breaking through the empirical dead-end created by the Gestalt view that physical analysis of the stimulus is pointless. In the past fifteen years there has been a renaissance in the study of form and pattern perception, and the pioneering attempts to create a multidimensional psychophysics of form must be given a large share of the credit for rekindling of interest in these problems. Beyond this the future of the psychophysical model is uncertain. It has already reached a high level of complexity in attempting to account for performance in relatively simple laboratory tasks. Little effort has been devoted to applying it to tasks in the real world. Perhaps it will have to give way to a model that can handle more complex data with greater parsimony. Even so, the methodological advances represented by the present development of the psychophysical model will be just as relevant for any model that might supplant it.

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PLANNING CONFERENCE AGENDA

OPENING SESSION

* Introductory remarks by Drs. Secrest, Arnoult, and Alluisi

* Goals of Project THEMIS: A review. Lynn Baker

An overview of machine and human pattern recognition. Selby Evans

THE RECOGNITION OF PATTERNS IN SPECIALIZED DATA

Graphical data processing. William Huber

* Pattern recognition of human physiological stress responses. Jesse Orlansky

* Pattern analysis and enhancement by schematic operators. Alexander Hoffman

Modeling the pattern recognition environment. Selby Evans and Robert Breckenridge

PATTERN RECOGNITION IN VISUAL DATA

BESRL image interpretation research. Thomas Jeffrey

Pattern recognition studies at the Ballistic Research Laboratories. Donald R. Menne and William Sacco

Applied perceptual problems in aircraft recognition and situation recognition. Dean Wright

Pattern recognition studies at AFCRL. Thomas Evans

Psychophysical models for pattern perception. Malcolm Arnoult and Richard Fenker

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* These presentations and discussions not included in this report.

OVERVIEW AND DEVELOPMENT OF ACTION PLANS

* Potential contributions of pattern recognition research to military needs: A survey and discussion of approaches. Robert Demaree

* Panel discussion: A review of previous sessions in relation to the projected symposium. Earl Alluisi, Malcolm Arnoult, Robert Demaree, and Selby Evans

* Open discussion by participants on how the projected symposium in particular, and basic pattern recognition research in general, can contribute to military needs, with specific attention to the implementation of such contributions.

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13. ABSTRACT

The Institute for the Study of Cognitive Systems at Texas Christian University is conducting a research program titled "Parameters of Human Pattern Perception" with Project THEMIS funding. This program's goals include development of a formal mathematical model of human pattern recognition behavior and subsequent computer simulation of the model.

Research on human pattern recognition has become increasingly more sophisticated during the past decade. At the same time substantial progress has been made in duplicating certain aspects of human pattern recognition capability in machines. Cross-fertilization between these two areas is a much-desired goal and the Texas Christian University research program is specifically planned to foster such mutual facilitation. The Institute, under the sponsorship of the U. S. Army Human Engineering Laboratories, is planning a symposium which will bring together leading workers in both fields.

To maximize the benefits of such a symposium to the Department of Defense, a planning conference was held in Fort Worth, Texas, 12-13 December 1968. This report summarizes presentations given at the planning conference.

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